AN ANALYSIS OF PRICING AND LEADTIME POLICIES WITHIN THE MARKETING/OPERATIONS INTERFACE

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To my dear parents,

Birgul and Ruchan Pekgun,

for their unconditional love and support...

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SUMMARY

In this thesis, we analyze the impact of the decentralization of price and leadtime decisions made by the marketing and production departments, respectively, in a make-to-order firm. We first study a monopoly environment, and find that in the decentralized setting, the total demand generated is larger, leadtimes are longer, quoted prices are lower, and the firm profits are lower as compared to the centralized setting. We show that coordination can be achieved using a transfer price contract with bonus payments, where both departments receive a fraction of the total revenues generated as a bonus payment. In the second study, we extend this work to a duopoly environment, where two firms compete on the basis of their price and leadtime quotes in a common market. We find that under intense price competition, firms may suffer from a decentralized structure, particularly under high flexibility induced by high capacity, where revenue based sales incentives motivate sales/marketing for more aggressive price cuts resulting in eroding margins.

We take the parameters of the demand models in the first two studies as constant, while estimating those parameters based on historical data is a very important problem in practice. In the last study of this thesis, we address the challenges encountered in estimating the price sensitivity of customers shifting focus to the passenger travel industry. We explore how to obtain better price elasticity estimates through an empirical study with an emphasis on the endogeneity problem, which arises as a result of the simultaneous determination of supply and demand. We show that if one does not account for endogeneity, price elasticities may induce an upward-sloping demand curve suggesting that high price produces high demand, or may be biased downward to the extent that elastic demand curves are incorrectly classified as inelastic. We show the improvement in price elasticities through an instrumental variable approach.

CHAPTER I

INTRODUCTION

Recent business trends and advances in consumer behavior modeling have shown that demand for goods and services, and in turn, the profits of the companies, are shaped by not only inventory policies and capacity allocation but also by price and leadtime decisions. Quoting the right price and the reliable leadtime to match supply and demand is especially important as many companies move from a make-to-stock to a make-to-order model to satisfy their customers' unique needs. There are numerous examples of companies, which lost significant amount of money due to pricing and leadtime decisions. Mercedes-Benz underestimated customers' willingness to pay when it first introduced SLC roadster in the early 1990s. As a result, it received more orders than it could fulfill within a reasonable leadtime. Over time, Mercedes-Benz gained more information about how much customers value its cars and substantially increased the price to align demand and capacity [38]. A well-known example for quoting reliable leadtimes is the case of seven online e-tailers, including Macys.com, Toysrus.com and CDNOW, that paid fines totaling $1.5 million to settle a Federal Trade Commission lawsuit over late deliveries made during the 1999 holiday season. The e-tailers promised delivery dates when fulfillment was not possible and failed to notify customers when shipments would be late.

Ideally, a firm should take a global perspective and coordinate its decisions on price and leadtime quotation for increased profitability. In reality, however, different divisions of large companies all too often fail to communicate on important business decisions [65]. Moreover, each function behaves to maximize its own interests, and assumes that this will also lead to maximization of the overall profit. Narayanan and Raman ([91]) point out that this assumption is in fact wrong and emphasize the importance of aligning the incentives of different functions: "Supply chains extend across several functions and many companies, each of which has its own priorities and goals. Yet all those functions and firms must pull in the same direction to ensure that supply chains deliver goods and services quickly and cost-effectively... If a company aligns the incentives of the firms in its supply chain, everyone will make higher profits."

Quoting the right prices to maximize revenue and leadtimes to ensure reliable delivery involves the decisions and actions of both marketing and manufacturing functions of a company. These functions may be different companies within a supply chain or different profit centers within the same company. In many companies, manufacturing is evaluated based on costs and operational efficiency while marketing is evaluated based on revenue and volume [6]. Misalignment of incentives usually imply decentralization of price, leadtime and capacity decisions. While several studies have noted improvements in business performance when marketing and manufacturing divisions work together [93, 78, 55], studies that measure the impact of the decentralization of price and leadtime decisions and suggest coordination mechanisms are lacking. This is important since depending on market conditions and its current workload, the firm may find it more profitable to offer customers shorter leadtimes at the expense of higher prices or vice versa. In this thesis, we analyze the impact of the decentralization of price and leadtime decisions for a make-to-order firm under a monopoly in Chapter 2 and a duopoly in Chapter 3. We model firm operations as an M/M/1 queue, and develop uniform delivery time guarantees. The marketing department makes pricing decisions to maximize its revenue, while production makes leadtime decisions with cost and delivery reliability concerns. Customer demand is modeled by a linear function that is decreasing in the quoted price and leadtime.

In Chapter 2, we find that in the decentralized setting, the total demand generated is larger, leadtimes are longer, quoted prices are lower, and the firm profits are lower as compared to the centralized setting. We explore coordination mechanisms and examine their robustness to estimation errors in the problem parameters. We also provide insights on the sensitivity of the optimal decisions with respect to market characteristics, sequence of decisions, and the firm's capacity level. We show that a decentralized setting with marketing as the leader would dominate one with production as the leader. In Chapter 3, we extend this work to a competitive environment, where two firms compete on the basis of their uniform delivery time guarantees and prices in a common market. Under this environment, a firm's generated demand is not only sensitive to its own quoted price and leadtime, but also to its competitor's price and leadtime. We explore if and when decentralization dominates centralization under competition. We model this problem as a two-stage game, where in the first stage, firms simultaneously choose their organizational structures so as to operate in a centralized or decentralized structure, and in the second stage, they simultaneously choose their price and lead-time decisions. We find that under intense price competition, where the intensity is characterized by the underlying parameters of market demand, firms may suffer from a decentralized structure, particularly under high flexibility induced by high capacity, where revenue based sales incentives motivate sales/marketing for more aggressive price cuts resulting in eroding margins. Particularly, when price competition is more intense than lead-time competition in the market, a centralized organizational structure is dominant for both firms in the duopoly.

We take the parameters of the demand models in Chapters 2 and 3 as constants, while estimating those parameters based on historical data is a very important problem in practice. Therefore, in Chapter 4, we address the problems encountered in estimating the price sensitivity of the customers in a revenue management context. We move our focus from a manufacturing/retail setting to the passenger travel industry, as market response models have been widely studied in retail industries, while studies in passenger travel contexts are lacking especially at a product level under availability controls dictated by revenue management systems. Over the past few years, the passenger travel industry has been transformed by the increasing availability of low-cost carriers/high-speed train services and customers becoming more conscious of low prices through the visibility offered by the internet [60, 22]. Thus, carriers tend to decrease the range of restrictions and offer a limited number of differentiated products. In this new environment, besides setting protection levels or bid-price controls for booking classes, revenue management systems need to be able to generate "what-if" scenarios, i.e., price-sensitive forecasts by departure date that indicate the expected level of demand across a range of possible price points. In order to better serve this purpose, accurate estimation of the price sensitivity of customers plays an important role.

In Chapter 4, we explore how to obtain better price sensitivity estimates through an empirical study based on the data of an international high speed rail operator. We particularly focus on the endogeneity problem, which arises as a result of the simultaneous determination of supply and demand. When carriers observe or anticipate high demand, they often react by raising their prices, which results in high price-high demand and low price-low demand pairs in the data. We show that if one does not account for endogeneity, price elasticities may induce an upward-sloping demand curve suggesting that high price produces high demand, or may be biased downward to the extent that elastic demand curves are incorrectly classified as inelastic. We show the improvement in price elasticities through an instrumental variable approach.

CHAPTER II

COORDINATION OF MARKETING AND PRODUCTION FOR PRICE AND LEAD-TIME DECISIONS

2.1 Introduction

In many firms, manufacturing is evaluated as a cost center that seeks lower costs and operational efficiency, while marketing is evaluated as a revenue center with control over price and other marketing elements [6, 63]. However, this is not necessarily an effective strategy. Dividing a firm into independent units for measuring performance on accounting terms may lead to misaligned incentives and suboptimal system performance [93]. Malhotra and Sharma ([78]) emphasize the need to align the manufacturing and marketing incentives with the firm's goals and objectives. Hausman *et al.* ([55]) empirically demonstrate that business performance is enhanced when manufacturing and marketing work together for goal attainment.

The two prominent aspects of customer service, namely, price and lead-time, involve the decisions and actions of both departments. Shapiro ([110]) identifies lead-times and cost control as two marketing/manufacturing areas of "necessary cooperation but potential conflict" among others. Dr. Karl Kempf, Intel Fellow and Director of Decision Technologies in Intel's Technology and Manufacturing Group, reports that different divisions of large companies all too often fail to communicate on important business decisions: "I have lost count of the number of times the sales and marketing guys have made a price move on a particular product only to find that manufacturing capacity fungibility is not what they expected and to capture the increased demand for the target product required cannibalization of a number of other products - it is not uncommon for this kind of problem to have a $100M negative impact overall (prior discussion could have minimized the impact)" [65].

Former Kozmo.com manager John C. Wu addresses the strategic importance of coordinated marketing and operations [137]. Kozmo.com was a web retailer that promised to deliver every order within an hour. Low prices were offered to attract customers despite the high fulfillment costs incurred as a result of their service commitment. Not surprisingly, Kozmo.com went out of business. According to AMR Research, companies on the leading edge of price management achieve their success by a centralized pricing function and the adjustment of sales incentives to include margin, not just volume [104].

In this chapter, we study the impact of the decentralization of the marketing and production departments of a make-to-order (MTO) firm, where pricing decisions are made by the marketing department and lead-time decisions by the production department. Although a shorter lead-time may attract more customers and generate more demand, it puts pressure on the firm's production resources. On the other hand, customers might be willing to wait longer if they are offered lower prices. Therefore, depending on market conditions and its current workload, the firm may find it more profitable to offer customers shorter lead-times at the expense of higher prices or vice versa. To capture the trade-off between price and lead-time, we model the demand as a function of both the price and lead-time sensitivity of the customer. Under the decentralized setting, given their incentives (objective functions) production chooses a lead-time subject to a service level constraint for reliable delivery, while marketing chooses a price. We formulate the problem as a Stackelberg game with two alternative decision making sequences, where production is the leader and marketing is the follower in the first setting, and marketing is the leader and production is the follower in the second setting. We address the following research questions:

1. What are the inefficiencies that result from the decentralization of price and lead-time decisions as quoted by marketing and production, respectively?

2. How can we design a coordination scheme that will align the incentives of marketing and production with the firm's overall objectives?

3. What is the impact of different market characteristics, decision-making sequences and capacity on the optimal decisions and overall profitability?

Our model where production and marketing/sales make the lead-time and price decisions, respectively, applies to several industries, especially to established production systems where the capacity is fixed.[1] In practice, even if the lead-time quote is communicated to the customers via sales/marketing (along with the price quote), the main input (or decision) about the lead-time quote usually comes from production. On the other hand, as the leader, marketing can influence production's lead-time decision via its price decision based on the potential demand to be generated, before communicating the quote to the customer.

The organization of this chapter is as follows. We begin by presenting a summary of the relevant literature. In Section 2.3, we discuss our model assumptions and introduce notation. We start our analysis with a centralized setting, where price and lead-time decisions are made by a single decision maker. We next present the decentralized settings, where marketing chooses the price and production chooses the lead-time according to their individual objectives. We compare the centralized and decentralized settings and analyze the sensitivity of the optimal decisions to problem parameters. In Section 2.4, we present a transfer price contract with bonus payments that provide the right incentives to both departments in order to achieve the centralized solution. In Section 2.5, we provide insights on including capacity as a decision variable. Section 2.6 concludes with a summary of insights.

2.2 Literature Review

There are two streams of research related to our work: (i) due-date management, and (ii) the marketing/production interface. For an extensive review on due-date management policies,

[1] There have been some examples in practice where marketing made lead-time decisions without consultations from production, but such practices have resulted in unsatisfied customers and significant losses for the firm. For example, Kirk Drummond, chief information officer of a leading food services and products provider Sysco, reports of situations where salespeople brought in huge last minute orders for next-day fulfillment without any advance warning to operations [61].

see [66]. Several researchers study the due date quotation problem taking into account shop-floor congestion at the time an order is placed and consider scheduling/sequencing decisions [44, 43]. Elhafsi and Rolland ([44]) consider a MTO manufacturing system, which consists of several processing centers that are subject to failures and repairs. Their model takes into account the congestion level of the shop floor at the time the order is placed in order to quote a delivery date within a prespecified time window with the minimum operating cost. They consider two types of customers as time-sensitive and cost-sensitive. Elhafsi ([43]) extends this work by introducing two options for each customer class: partial deliveries allowed and not allowed. In order to quote short and reliable lead-times to an upcoming order, service level constraints are applied such as the percentage of orders filled on-time or job tardiness [116, 59]. Spearman and Zhang ([116]) examine the problem of minimizing the average lead-time in a multi-stage production system. They consider two types of service level constraints as the fraction of tardy jobs, and the average job tardiness. Hopp and Sturgis ([59]) study the same problem subject to a target service level as the percent of orders filled on-time using a control chart method. Some of the studies consider order selection decisions, where the probability that an arriving customer places an order decreases as the quoted lead-time increases [41, 40]. Duenyas and Hopp ([41]) study this problem under first-come-first-serve (FCFS) and other scheduling policies where the lead-time is dictated by the market and where firms are able to compete on the basis of lead-time. Duenyas ([40]) extends this work to multiple customer classes with different net revenues and lead-time preferences. The firm incurs a penalty for an order not filled on time. Finally, a small number of papers consider price and lead-time decisions simultaneously [42, 87, 86, 101, 132, 26, 134, 27].

More relevant to our work are the papers that consider price and lead-time decisions simultaneously in steady-state. Palaka *et al.* ([95]) study a firm, where customer demand is treated as linear in the quoted price and lead-time. Firm operations are modelled as an M/M/1 queue with FCFS sequencing. The objective is to maximize revenues less total variable production costs, congestion related costs and lateness penalty costs subject to a service level constraint, which specifies the minimum probability of meeting the quoted lead-time. The authors show the impact of changing parameter values on the optimal decisions of a firm and discuss the robustness of firm profits to misestimation of the parameters. So and Song ([114]) use the log-linear Cobb-Douglas demand function to model the demand in a similar setting, but do not include congestion or lateness penalty costs in the objective function. Boyaci and Ray ([21]) extend the previous two models to the case of two substitutable products for which dedicated capacities are allocated. Finally, Ray and Jewkes ([105]) study a variant of the linear customer demand model in [95] by treating price as a function of lead-time. These papers develop uniform delivery time guarantees as opposed to quoting a lead-time to each upcoming order with regard to the current state of the system, which constitutes a major distinction from the first set of papers mentioned.

In this chapter, we model customer demand as a linear function of price and lead-time as in [95], but we only consider variable production costs as in [114]. The desirable properties of the linear demand function are discussed in [95]. One desirable property is that the price elasticity of demand is increasing in both price and lead-time. The lead-time elasticity is higher at higher prices and quoted lead-times. Another desirable property is the separability of price and lead-time, which reflects customers' perception of time and money as substitutes. While previous papers assume a centralized decision maker controlling price and lead-time, our main contribution is in demonstrating the inefficiencies that result when price and lead-time are quoted by two independent functions within a firm. We show that a transfer price contract with bonus payments motivates marketing and production to generate higher profits with an efficient output that matches the centralized solution. Our results for the centralized setting, which we use as a benchmark, are consistent with those found in [95]. However, we provide a more detailed analysis on pricing decisions.

The second stream of research concentrates on the joint decision making of the marketing and operations functions of a firm. For an early review of marketing and production coordination, the reader is referred to [46]. Several of the papers in this stream focus on pricing and/or replenishment decisions [45, 35, 84, 102, 67, 69, 73, 53]; however, they do not consider lead-time decisions. Eliashberg and Steinberg ([45]) and Kumar *et al.* ([69]) study a distribution channel in a multi-period deterministic demand setting, where the manufacturer has to decide on the production and inventory quantities and the price to be quoted to the distributor. There is decentralization in the marketing and production functions of the distributor in [69] as different from [45], where the marketing department makes pricing decisions to maximize its profits while the production function makes procurement decisions from the manufacturer to minimize inventory and processing costs. Customer demand is modeled as a linear function of the distributor's selling price. Gupta and Weerawat ([53]) study variants of revenue sharing contracts for a manufacturer, whose revenues depend on order delays, to influence the replenishment decisions of its supplier. The selling price and the demand rate are assumed to be exogenous, and the operational decision variable is the inventory level. Li and Atkins ([73]) compare different scenarios for the decision making structure in a firm in a newsvendor setting, where marketing is the dominant function, production is the dominant function, or both have equal power. Dewan and Mendelson ([35]) and Mendelson and Whang ([84]) develop optimal pricing schemes in a queueing setting for aligning the objectives of user departments that compete for capacity taking into account user delay costs and capacity costs. Porteus and Whang ([102]) and Kouvelis and Lariviere ([67]) use internal market mechanisms in a newsvendor setting for manufacturing capacity where optimal incentive plans are derived to induce system-optimal actions from marketing and manufacturing via principal-agent theory. The selling price is exogenous in the first paper, and modeled with an inverse demand function in the latter.

Some of the work in this area consider coordination issues for other types of decisions. De Groote ([33]) studies a firm, where the marketing department selects the optimal design of product variety, while the manufacturing department decides on the process flexibility. Balasubramanian and Bhardwaj ([6]) model a duopoly in which firms with decentralized marketing and manufacturing functions with conflicting objectives compete on the basis of price and quality. [47], [28], [56] and [112] study the lead-time quotation problem within the marketing/operations interface. However, they do not consider pricing decisions. A recent paper by Liu *et al.* ([74]) considers price and lead-time decisions in a two-firm setting; a supplier and a retailer within a supply chain, where the supplier also needs to choose the transfer price. In contrast to our focus on evaluating marketing as a revenue center and production as a cost center, they focus on the inefficiencies that result from the double marginalization in the supply chain. Although they find that decentralization leads to lower profits as we do, since the decentralized structures in the two papers are different, they show that under the decentralized setting prices are higher, lead-times are shorter and demand is lower, which is exactly the opposite of what we find in our study. Moreover, they do not consider coordinating mechanisms, whereas we show that coordination in our setting can be achieved through a transfer price contract with bonus payments. In this respect, our work is the first to study marketing and production coordination for price and lead-time decisions.

2.3 The Model

We consider a firm that serves customers in an MTO fashion. Capacity is assumed to be constant, while price and lead-time are decision variables. We include capacity as a decision variable in Section 2.5. It has been shown in the literature that for high service levels the tail of the waiting time distribution is approximated well by the exponential distribution even for a G/G/s queue [114]. Thus, the firm's operations are modeled as an M/M/1 queue with mean production rate, μ, and mean arrival rate, λ. We refer to the mean production rate, μ, as the capacity of the system. Subscript C denotes the centralized setting, while subscripts P and M denote the decentralized setting with production as the leader and marketing as the leader, respectively. We use the following notation throughout the text:

Parameters:

a : maximum attainable demand (market potential) corresponding to zero price and zero lead-time

b : price sensitivity of demand

c : lead-time sensitivity of demand

m : unit production cost

μ : capacity of the production system (service rate)

s : service level defined as the probability of meeting the quoted lead-time

k : used for computational simplicity, $k = \ln(1/(1 - s))$

Decision Variables

p_j : price quoted by the marketing department ($j = C, P, M$)

L_j : lead-time quoted by the production department ($j = C, P, M$)

$D(p, L)$: expected demand generated by the quoted price p and quoted lead-time L

λ_j : mean arrival (demand) rate ($j = C, P, M$)

π_j : profit achieved by the firm ($j = C, P, M$)

π^{MR}, π^{PR} : profit achieved by the marketing and production departments, respectively

r : incentive per unit offered to the production department for positive demand

w : transfer price charged per unit by production to marketing

α_1, α_2 : the fraction of revenue offered to marketing and production as a bonus payment, respectively

K : unit capacity cost (to be used in Section 2.5).

Our model assumptions are as follows:

A1. There are no holding or lateness penalty costs; there is a variable production cost.

A2. Expected demand rate, $D(p, L)$, is linear in price, p, and lead-time, L:

$$D(p, L) = a - bp - cL$$

where $b > 0$ and $c > 0$.

A3. (**Positive Demand Assumption**) There is positive demand for the firm to provide its services when the smallest reasonable price, m, and the shortest lead-time that satisfies the service level constraint, (k/μ), are chosen: $D(m, (k/\mu)) = a - bm - ck/\mu > 0$. Note that if this assumption is not satisfied, the firm can never generate positive profits, and hence, the problem becomes trivial.

A4. All the parameters of the system are common knowledge to marketing and production.

2.3.1 The Centralized Setting (Model C)

In the centralized setting, the marketing and production decisions are considered simultaneously with the objective of maximizing profit.

$$\max_{(\lambda_C, p_C, L_C) \geq 0} \quad \lambda_c (p_C - m)$$

$$s.t. \quad 1 - e^{-(\mu - \lambda_C) L_C} \geq s \tag{1}$$

$$\lambda_c \leq a - bp_c - cL_c \tag{2}$$

$$\lambda_c \leq \mu \tag{3}$$

Constraint (1) states that the probability of meeting the quoted lead-time should be at least as large as the required service level. Constraint (2) ensures that the mean demand rate served by the firm does not exceed the demand generated by the quoted price and lead-time. Constraint (3) is the stability condition.

The optimal solution is identified by the following proposition.

Proposition 1 *The optimal demand generated under the centralized setting is given by the unique root of $f_C(\lambda_C)$, i.e., $f_C(\lambda_C^*) = 0$, on the interval $[0, \mu]$, where*

$$f_C(\lambda_C^*) = (a - 2\lambda_C^* - mb)(\mu - \lambda_C^*)^2 - ck\mu \tag{4}$$

The optimal lead-time and the optimal price are then given by $L_C^* = \frac{k}{\mu - \lambda_C^*}$ *and* $p_C^* = (a - \lambda_C^* - cL_C^*)/b$*, respectively.*

These results are a special case of those found in [95] for the fixed capacity case, when there are no holding or lateness costs.

2.3.2 The Decentralized Setting, Production Leader (Model P)

In this section, we consider the case where the production and marketing departments operate in a decentralized setting making their decisions based on individual incentives. We model the sequence of decisions as a Stackelberg game, where production moves first and chooses a lead-time that maximizes its profit subject to the service level constraint. Marketing observes this lead-time decision before quoting price with the objective of maximizing its own profit. We assume initially that no production-related costs are incurred by the marketing department. Hence, the objective function of marketing is given by the revenue of the firm.

We solve for subgame-perfect Nash equilibrium by backwards induction starting with marketing's problem.

$$\max_{p_P \geq m} \quad \pi_P^{MR} = p_P(a - bp_P - cL_P)$$

We find the optimal price and demand as follows:

$$p_P^*(L_P) = \max\left\{m, \frac{a - cL_P}{2b}\right\} \text{ and } \lambda_P^*(L_P) = a - bp_P^*(L_P) - cL_P \tag{5}$$

The optimal demand, $\lambda_P^*(L_P)$ derived from marketing's best response, $p_P^*(L_P)$, to production's lead-time decision is then used in production's problem. The cost term of production's objective function reflects the cost incurred by the firm. However, one should note that if this was solely a cost minimization problem, production would quote the longest possible lead-time, which satisfies the service level constraint driving demand to zero. Therefore, there should be an incentive, r, given by the firm to production per unit of demand realized.

$$\max_{0 \le L_P \le \frac{a}{c}} \quad \pi_P^{PR} = (r - m)\lambda_P^*(L_P) \tag{6}$$

$$s.t. \quad \left(\mu - \lambda_P^*(L_P)\right) L_P \ge k \tag{7}$$

In order to generate strictly positive demand, r would range from $m \le r \le p_P^*$, given the linearly decreasing structure of π_P^{PR} in L_P. A reasonable incentive that we choose is $r = p_P^*(L_P)$, which turns production's problem into the firm's overall problem in the decentralized setting. Note that this objective function is consistent with the concept of creating pseudo-profit centers within the firm, i.e., associating revenues artificially with cost centers, as discussed in [93].

Proposition 2 *The optimal solution to the decentralized setting, P, is given by:*

(i) *If $a > 2mb$ and $\mu > \mu^0 = bm + \frac{ck}{a-2mb}$, then $L_P^* = \frac{(a-2\mu)+\sqrt{(2\mu-a)^2+8ck}}{2c}$ and $p_P^* = \frac{a-cL_P^*}{2b}$.*

(ii) *Otherwise, $p_P^* = m$ and $L_P^* = \frac{a-bm-\mu+\sqrt{(\mu-a+bm)^2+4ck}}{2c}$, and the firm will be selling at cost.*

Proposition 2 states that there is a minimum capacity requirement, $\mu > \mu^0$, for the production department to generate positive profits under this decentralized setting. Long lead-times under restricted capacity motivate marketing to quote low prices in order to maximize its profit, which may not be sufficient to cover production costs. Therefore, in order for production not to drive demand to zero, the price quoted by marketing needs to be at least as large as the unit production cost. Note that, in practice, this would correspond to misaligned incentives leading to suboptimal performance.

2.3.3 The Decentralized Setting, Marketing Leader (Model *M*)

Under this setting, marketing moves first and chooses a price that maximizes its revenue. Observing this price, production quotes a lead-time with the objective of maximizing its profit subject to the service level constraint. We start with production's problem and offer the price quoted by marketing as an incentive to production as in Model P.

$$\max_{0\le L_M \le \frac{a-bp_M}{c}} \quad \pi_M^{PR} = \pi_M = (p_M - m)(a - bp_M - cL_M) \tag{8}$$

$$s.t. \quad (\mu - (a - bp_M - cL_M))\, L_M \ge k \tag{9}$$

As the objective function is linearly decreasing in L_M, Constraint (9) is tight at optimality, and assuming $p_M \ge m$, the optimal lead-time is found as:

$$L_M^*(p_M) = \frac{(a - bp_M - \mu) + \sqrt{(a - bp_M - \mu)^2 + 4ck}}{2c} \tag{10}$$

Marketing's problem is given by:

$$\max_{p_M \ge m} \quad \pi_M^{MR} = p_M(a - bp_M - cL_M^*(p_M))$$

As long as the unique maximizer of π_M^{MR} over the interval $[0, (a\mu - ck)/b\mu]$ is at least m, then we can characterize the optimal solution by the following proposition. Otherwise, the firm will be selling at cost.

Proposition 3 *The optimal demand under decentralized setting M is given by the unique root of $f_M(\lambda_M)$ on the interval $[0, \mu]$, where*

$$f_M(\lambda_M^*) = (a - 2\lambda_M^*)(\mu - \lambda_M^*)^2 - ck\mu \tag{11}$$

The optimal lead-time and the optimal price are then given by $L_M^* = \frac{k}{\mu - \lambda_M^*}$ and $p_M^* = (a - \lambda_M^* - cL_M^*)/b$, respectively.

2.3.4 Comparison of the Decentralized and Centralized Settings

In this section, we discuss the inefficiencies due to decentralization of pricing and lead-time decisions and compare the centralized and decentralized settings.

Proposition 4 *The optimal decisions of the centralized setting (C) and the decentralized settings where production is the leader (P) and where marketing is the leader (M) are such that: (i) $\lambda_C^* < \lambda_M^* \le \lambda_P^*$ (ii) $L_C^* < L_M^* \le L_P^*$ (iii) $p_C^* > p_M^* \ge p_P^*$ (iv) $\pi_C^* > \pi_M^* \ge \pi_P^*$.*

As long as it is given a positive margin, production quotes the tightest reliable lead-time given its available capacity and the required service level. As marketing's incentive is based on revenue irrespective of the production costs, it is motivated to create more demand than the centralized firm, which requires longer lead-times and lower prices.

When marketing is the follower in the decentralized firm (P), it responds to longer lead-times by decreasing prices, as it can be seen from its best response function (Equation (5)), which creates a large volume of demand but also high production costs. On the other hand, in M, marketing can anticipate production's best response as the leader, where production quotes lower lead-times to higher prices (Equation (10)). Thus, marketing can choose a higher price to motivate production to satisfy as much demand as possible without increasing lead-times significantly.

Proposition 5 *In a decentralized setting, highest revenues are generated when marketing is the leader, while highest volume is generated when production is the leader. The firm would prefer having marketing rather than production as the leader for generating more profits and quoting higher prices and lower lead-times in a decentralized setting.*

The aggressive response of marketing in P results in the highest volume among all three settings. However, low prices are not sufficient to make up for the high production costs, and this setting generates the lowest profits. When marketing is the leader (M), its influence on production helps to achieve highest revenues. However, costs also increase and overall, lower profits are generated as compared to the centralized setting. Thus, our analysis shows that employing a revenue or volume-based incentive mechanism for marketing does not lead to optimal profits. Note that the dominance of the decentralized setting with marketing as leader over the one with production as the leader is consistent with the findings in [73], where marketing and production make pricing and replenishment decisions, respectively, and misalignment of incentives within the firm can be mitigated through having marketing as the dominant function. However, in our case we see that the two functions can still not achieve the centralized solution without a coordinating mechanism. Even when there are no capacity restrictions and no service level constraints, the profit difference between the centralized and decentralized solutions is $\frac{m^2 b}{4}$, i.e., constant.

Sensitivity of the optimal decisions $L^*_\cdot$, $p^*_\cdot$ and $\lambda^*_\cdot$, and the optimal profit $\pi^*_\cdot$ to problem parameters for the centralized and decentralized settings is given in Table 1 assuming that the problem parameters are such that $p^*_M > m$ and $p^*_P > m$. For most cases, it can be seen from Table 1 that the direction of change in the optimal decisions and profit is independent of the decision-making paradigm (i.e., centralized or decentralized). The cases where the behavior of the optimal price (and profit for M) changes conditionally are indicated by a "?". We demonstrate these conditions analytically or numerically further in the text.

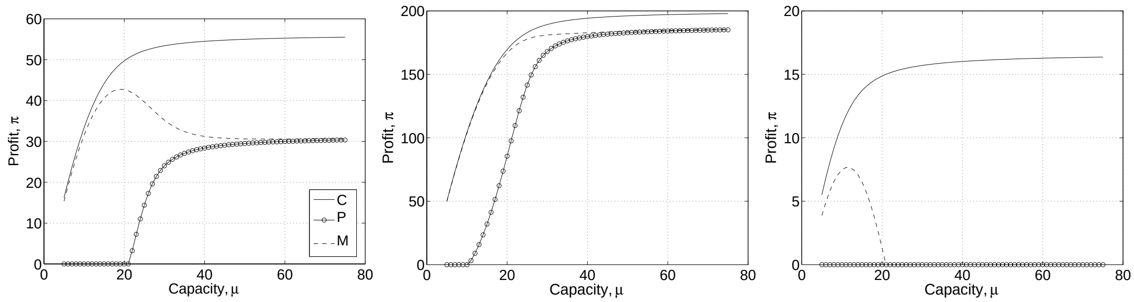
Table 1: Sensitivity analysis on optimal decisions and profit

	Centralized				**Decentralized, *P***				**Decentralized, *M***			
	$\lambda^*_{\mathbf{C}}$	$\mathbf{L}^*_{\mathbf{C}}$	$\mathbf{p}^*_{\mathbf{C}}$	$\pi^*_{\mathbf{C}}$	$\lambda^*_{\mathbf{P}}$	$\mathbf{L}^*_{\mathbf{P}}$	$\mathbf{p}^*_{\mathbf{P}}$	$\pi^*_{\mathbf{P}}$	$\lambda^*_{\mathbf{M}}$	$\mathbf{L}^*_{\mathbf{M}}$	$\mathbf{p}^*_{\mathbf{M}}$	$\pi^*_{\mathbf{M}}$
$a \nearrow$	$\nearrow$	$\nearrow$	$\nearrow$	$\nearrow$	$\nearrow$	$\nearrow$	$\nearrow$	$\nearrow$	$\nearrow$	$\nearrow$	$\nearrow$	$\nearrow$
$b \nearrow$	$\searrow$	$\searrow$	$\searrow$	$\searrow$	-	-	$\searrow$	$\searrow$	-	-	$\searrow$	$\searrow$
$c \nearrow$	$\searrow$	$\searrow$	?	$\searrow$	$\searrow$	$\searrow$	$\searrow$	$\searrow$	$\searrow$	$\searrow$	?	?
$m \nearrow$	$\searrow$	$\searrow$	$\nearrow$	$\searrow$	-	-	-	$\searrow$	-	-	-	$\searrow$
$s \nearrow$	$\searrow$	$\nearrow$	?	$\searrow$	$\searrow$	$\nearrow$	$\searrow$	$\searrow$	$\searrow$	$\nearrow$	?	?
$\mu \nearrow$	$\nearrow$	$\searrow$	?	$\nearrow$	$\nearrow$	$\searrow$	$\nearrow$	$\nearrow$	$\nearrow$	$\searrow$	?	?

Observation 1 *In the decentralized settings, the quoted lead-time is not affected by a change in b or m as long as production receives a positive margin, given marketing's best response in price. As marketing does not consider production costs, the optimal price is independent of a change in m. Moreover, an increase in b is met by a decrease in the quoted price. Thus, the generated demand is not affected by a change in b or m.*

We next discuss the cases where the behavior of the optimal price (and profit for M) changes conditionally. In all numerical demonstrations, we use $a = 50$, $b = 4$ $c = 4$ $m = 5$ $\mu = 25$ and $s = 0.95$ unless otherwise stated.

Figures 1 (i) and 2 (i) show a comparison of the profits and prices, respectively, under C, P and M at different capacity levels. We observe that for low-medium capacity levels, M



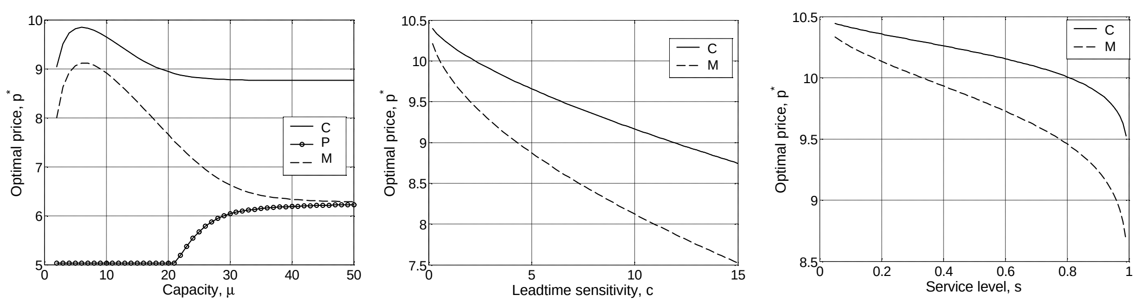
(i) (b = 4) **(ii)** (b = 2) **(iii)** (b = 6)

Figure 1: Comparison of Profits at Different Capacities

performs very close to C, while as the capacity increases, M deviates from C and converges to P. Under P, at low capacities production quotes long lead-times to which marketing responds with low prices, and up to a certain capacity level, the firm sells at cost and makes no profit. As more capacity becomes available, marketing responds to shorter lead-times by increasing prices and the profits also increase. Under M, marketing chooses a higher price as compared to P, anticipating production's response under tight capacity as the leader. As capacity increases, production can quote lower lead-times and more demand can be met. Thus, marketing's response as the leader gets closer to its response as the follower, which results in lower prices and profits as compared to the centralized setting. From Figure 2 (i), we can see that higher capacity does not necessarily result in charging higher under C or M. Price increases in μ up to a certain point in order to quote shorter lead-times within a tight capacity interval. As capacity increases, lower prices are quoted to increase demand. However, decentralization results in a sharper decrease in the quoted price. Note that price stabilizes as it approaches the unconstrained solution, i.e., $\frac{a+mb}{2b}$ for C and $\frac{a}{2b}$ for M under ample capacity, which is reached at $(a - mb)$ for C and a for M.

Observation 2 *Higher capacity results in higher flexibility and higher profits for a centralized firm. However, higher capacity does not necessarily result in higher profits for a decentralized firm.*

In Figures 1 (ii) and (iii), we explore the effect of b on the deviation of the decentralized profits from the centralized profit. Note that the optimality equation for λ_M^* (Equation (11)) is very similar to the optimality equation for λ_C^* (Equation (4)), but is independent of m and b. The optimal demand under P is also not affected by a change in m or b. Thus, we expect the deviation in profits to decrease as m and/or b decreases. A decrease in m alleviates the adverse effect of low prices on margin, while a decrease in b motivates marketing for less aggressive price cuts. In Figure 1(ii), we observe that at a lower b, M tracks C more closely, and the gap between the centralized and both decentralized settings decreases as the capacity increases. On the other hand, when b increases in Figure 1(iii), the firm needs to sell at cost for all capacity levels when production is the leader, while positive profit can be obtained within a tight capacity interval when marketing becomes the leader. We observe similar results when m changes rather than b. In summary, *when marketing is the leader, the profit difference from the centralized solution may not be significant under tight capacity and when b and/or m is low.* The following proposition summarizes the



(i) ($c = 4,\ s = 0.95$) **(ii)**($\mu = 8,\ s = 0.95$) **(iii)**($\mu = 8,\ c = 4$)

Figure 2: Price vs. Capacity, Lead-time Sensitivity and Service Level (Low Capacity)

behavior of the optimal price, p_i^*, with respect to lead-time sensitivity, c, and service level, s for $i = C,\ M$. Let $x_C = mb$ and $x_M = 0$. We define capacity levels $\mu \leq \frac{a-x_i}{3}$ as low, $\mu \in \left(\frac{a-x_i}{3}, a - x_i\right)$ as medium and $\mu \geq (a - x_i)$ as high for $i = C,\ M$.

Proposition 6 *When $\mu \in \left(\frac{a-x_i}{3}, a - x_i\right)$, i.e., capacity is medium,*

(i) *p_i^* increases in c up to a threshold, c_i^0, and then decreases, where $c_i^0 = \frac{1}{k\mu}\left(\frac{a-x_i-\mu}{2}\right)\left(\frac{a-x_i-3\mu}{4}\right)^2$.*

(ii) *p_i^* increases in s up to a threshold, s_i^0, and then decreases, where $s_i^0 = 1 - \frac{1}{e^{k_i^0}}$ and $k_i^0 = \frac{1}{c\mu}\left(\frac{a-x_i-\mu}{2}\right)\left(\frac{a-x_i-3\mu}{4}\right)^2$.*

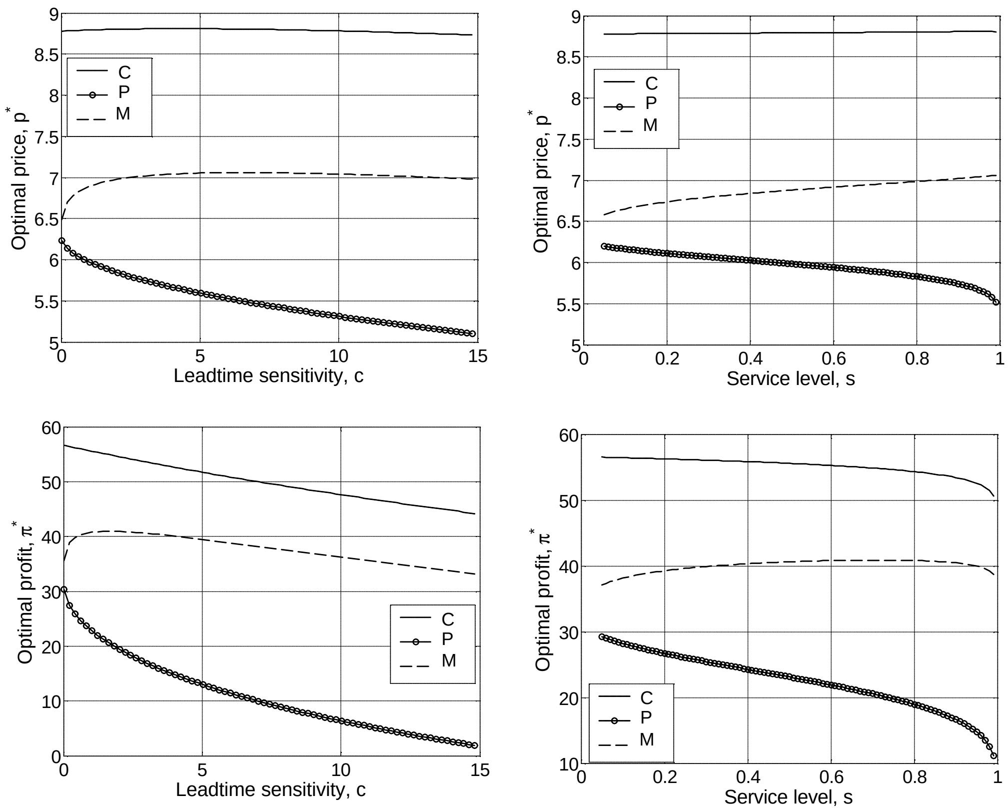
When $\mu \notin \left(\frac{a-x_i}{3}, a-x_i\right)$, i.e., capacity is low or high, p_i^* decreases in c and in s.

Note that low, medium, and high capacities are defined with respect to the market potential for both C and M, but also depend only on the unit production cost and price sensitivity for C. Under high capacity, lead-times are already low and price is decreased to capture more demand as c or s increases, although the change is relatively minor. At low capacity levels, it is not possible to shorten the lead-time further as c increases, while longer lead-times are required as s increases. Thus, the firm needs to decrease its quoted price in order to attract customers. From Figures 2 (ii) and (iii), we can see that under "low" capacity the price decrease under M is more aggressive than under C and the gap between the two settings increases as c or s increases. At medium capacity levels, quoted price under C and M increases in c and s up to a threshold, where μ is sufficient for charging a higher price for better service. However, beyond this point, the quoted lead-time can only be decreased slightly in c, and has to be increased sharply in s, given the capacity. Thus, the quoted price decreases to attract more customers. Note that when s_C^0 or c_C^0 is beyond the feasible range for s or c, respectively, given the parameters of the system, we may only observe an increasing behavior in price. This contradicts with the result found in [114] for the fixed capacity case, which states that a higher service level implies a lower price.

Observation 3 *When marketing is the leader, the decentralized firm may experience an increase in profits at medium capacity levels as the lead-time sensitivity or the service level increases.*

We demonstrate this observation in Figure 3 comparing the three settings for quoted prices and profits. For the centralized firm, prices are relatively stable. Thus, the price increase is less effective than the decrease in the generated demand as c or s increases, and the profits decrease. On the other hand, under M, as marketing is evaluated based on revenue, price increase may be more effective than the demand decrease, and the decentralized firm may benefit from higher service levels or higher lead-time sensitivity of the customer demand.

Note that when production is the leader, price and demand both decrease in c and s, hence, the profits also decrease.



(i) ($s = 0.95$) **(ii)** ($c = 4$)

Figure 3: Price and Profit vs. Lead-time Sensitivity and Service Level (Medium Capacity)

2.4 Transfer Price with Bonus Payments (TB) Contract

In this section, we propose a transfer price contract with bonus payments (hereafter the TB contract) for coordinating marketing and production, where marketing pays w to production for each unit produced, and both departments receive a bonus payment as the fraction of the total revenues generated. We use subscript $i = P,\ M$ to represent production as the leader and marketing as the leader, respectively. Note that total firm profits are given by $\pi_i = \pi_i^{PR} + \pi_i^{MR}$.

We study a flexible mechanism where the fractions of revenues received by the two departments do not necessarily add to 1. Let $\alpha_1 > 0$ denote the share for marketing and

$\alpha_2 \geq 0$ the share for production. We assume that $\alpha_1 + \alpha_2 \leq 1$.

2.4.1 Solution under the TB Contract

Marketing's problem is:

$$\max_{p_i \geq m} \quad \pi_i^{MR} = (\alpha_1 p_i - w)(a - bp_i - cL_i)$$

Production's problem is:

$$\begin{aligned} \max_{L_i \geq 0} \quad & \pi_i^{PR} = (\alpha_2 p_i + w - m)(a - bp_i - cL_i) \\ s.t. \quad & (\mu - (a - bp_i - cL_i))\, L_i \geq k \end{aligned} \tag{12}$$

We solve for the subgame-perfect Nash equilibrium by backwards induction starting with the follower's problem in each setting.

Proposition 7 *Decentralized setting $i = P, M$ under the TB Contract has a nontrivial optimal solution with positive profit if and only if for every α_1 fraction of revenue for marketing and an accordingly chosen transfer price, $w_i^{min}(\alpha_1) \leq w \leq \alpha_1\left(\frac{a}{b} - \frac{ck}{\mu b}\right)$, α_2 is chosen such that $\alpha_{2i}^{min}(\alpha_1, w) \leq \alpha_2 \leq (1 - \alpha_1)$, where $\alpha_{2i}^{min}(\alpha_1, w)$ ensures that production receives a positive margin, i.e., $\alpha_2 p_i^* + w - m \geq 0$, and $w_i^{min}(\alpha_1)$ is the minimum transfer price that ensures $\alpha_2 \leq (1 - \alpha_1)$. For these (α_1, α_2, w) combinations:*

(i=P) Production Leader, Marketing Follower:

The optimal decisions are given by

$$L_P^* = \frac{a - 2\mu - wb/\alpha_1 + \sqrt{(a - 2\mu - wb/\alpha_1)^2 + 8ck}}{2c},$$
$$p_P^* = \frac{a - cL_P^*}{2b} + \frac{w}{2\alpha_1}, \quad \lambda_P^* = \frac{a - cL_P^*}{2} - \frac{wb}{2\alpha_1}.$$

(i=M) Marketing Leader, Production Follower:

The optimal demand is given by the unique root of $f_M(\lambda_M)$ over the interval $[0, \mu]$, where

$$f_M(\lambda_M^*) = (a - 2\lambda_M^* - wb/\alpha_1)(\mu - \lambda_M^*)^2 - ck\mu \tag{13}$$

The optimal lead-time and price are $L_M^* = \frac{k}{\mu - \lambda_M^*}$ and $p_M^* = (a - \lambda_M^* - cL_M^*)/b$.

Note that the maximum transfer price that can be charged is decreasing in service level, which seems counter-intuitive. However, this is only an upper bound to ensure that positive demand is generated. One should also note that the set of feasible contract parameters do not necessarily need to be identical for both decentralized settings.

2.4.2 Coordination under the TB Contract

In order to achieve coordination, we need to choose the contract parameters such that the demand generated in the decentralized settings is equal to that in the centralized setting, i.e., $\lambda_i^* = \lambda_C^*$. This demand will also guarantee the lead-time and price quoted in the centralized setting, since they are uniquely determined by the demand level. The following proposition characterizes the coordinating contract parameters for both decentralized settings.

Proposition 8 *Under the TB contract, there exists a unique coordinating transfer price* $w_P^* = \alpha_1 \left(\frac{a - 2\lambda_C^* - \frac{ck}{\mu - \lambda_C^*}}{b} \right)$ *under* P *and* $w_M^* = \alpha_1 m$ *under* M *for a given* $0 < \alpha_1 \leq 1$ *fraction of the revenue for marketing and* $\alpha_2 \in \left[\alpha_{2i}^{min}(\alpha_1, w_i^*), (1 - \alpha_1) \right]$ *fraction of the revenue for production.*

It can be observed from Proposition 8 that the coordinating transfer price only depends on α_1 and m when marketing is the leader, while it depends on all problem parameters except m and requires knowledge of the centralized demand level when production is the leader. Moreover, $w_P^* > \alpha_1 m = w_M^*$, i.e., marketing needs to pay a larger transfer price to production as the follower than as the leader. One should also note that the coordinating transfer price, w_i^*, increases linearly in α_1 under both decentralized settings. In other words, as marketing gets a higher fraction of the revenue, it needs to pay a higher per unit transfer price to production.

Under coordination, marketing receives α_1 fraction of the centralized revenue. Proposition 9 indicates that the fraction of the centralized profit it achieves is not the same under P and M.

Proposition 9 *The fraction of the centralized profit that is realized by marketing is α_1 when it is the leader and less than α_1 when it is the follower.*

Note that when production is the leader, the fraction of the centralized profit realized by marketing increases with capacity. Moreover, as the profit achieved by marketing reduces to $\alpha_1 \frac{(\lambda_C^*)^2}{b}$ and λ_C^* is increasing in μ, the absolute profit achieved by marketing is also increasing in μ. Hence, marketing becomes better off with higher capacity.

Observation 4 *For a given α_1 and the coordinating transfer price as described in Proposition 8, production prefers $\alpha_2 = (1 - \alpha_1)$ to generate higher profits under both decentralized settings. In this case, the fraction of the centralized profit that is realized by production is equal to $(1 - \alpha_1)$ when it is the follower and greater than $(1 - \alpha_1)$ when it is the leader.*

The TB contract with parameters as described in Observation 4, where $\alpha_1 + \alpha_2 = 1$, has been frequently discussed in the literature as the "Revenue Sharing Contract". This contract provides flexible allocation of profits between marketing and production, where the fraction of profit marketing achieves ranges from 0 to $\frac{\lambda_C^*}{(p_C^* - m)b}$ under P and anywhere from 0 to 1 under M.

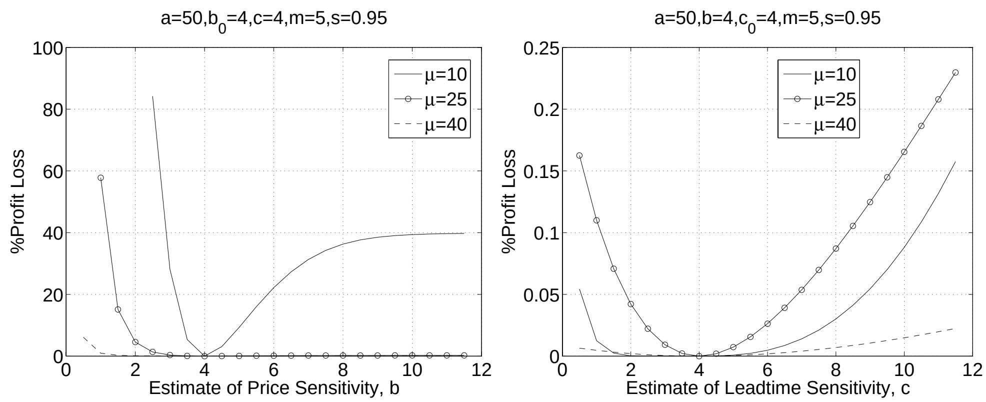
Another special case of the TB contract is the transfer price-only contract with $\alpha_1 = 1,\ \alpha_2 = 0$, which has been addressed in the literature as the "Wholesale Price Contract". From Proposition 8, we find that the unique coordinating transfer price is given by $w_P^* = \left(\frac{a - 2\lambda_C^* - \frac{ck}{\mu - \lambda_C^*}}{b}\right)$ for P and $w_M^* = m$ for M. Note that when marketing is the leader, production breaks even, i.e., generates zero profit under this contract. However, we see that replacing the objective function of marketing with the firm profit rather than the firm revenue will achieve the centralized solution. Therefore, the proposed contract is in line with the view of industry experts on adjusting the sales incentives to include margin [104].

Finally, under a TB contract with no transfer price ($w = 0$), coordination cannot be achieved under either of the decentralized settings. In fact, such a contract generates the same solution as the original decentralized settings, and thus, it is not possible to coordinate the two departments. For an extensive review of supply chain contracts, the reader may refer to [23].

2.4.3 Robustness of the TB Contract

In this section, we examine the robustness (in terms of percent profit loss) of the TB contract to estimation errors in the price sensitivity and lead-time sensitivity of the customers. Note that when marketing is the leader, the coordinating transfer price is independent of the problem parameters, except m. Thus, misestimation of the demand parameters may only affect the feasibility of α_2 for a given α_1, which would not constitute a problem under a Revenue Sharing Contract with $\alpha_2 = 1 - \alpha_1$. However, when production is the leader, misestimating the demand parameters may have a significant effect on choosing the correct coordinating transfer price. Thus, we investigate the robustness of the TB contract for decentralized setting P and we use a transfer price-only contract with $\alpha_1 = 1$ and $\alpha_2 = 0$ for demonstration purposes. As the general contract setting offers more flexibility, its robustness cannot be expected to be worse than this contract.

We perform the analysis as follows: (i) Calculate the transfer price that coordinates production and marketing at an estimated value of the parameter, and (ii) calculate the optimal decisions of the two parties under the contract with the true parameter value using the decentralized setting, P. Figure 4 shows the percent profit loss caused by the estimation errors in b and c. We observe that *underestimation of b or c leads to higher profit losses as compared to overestimation*. When b (c) is underestimated, the chosen transfer price motivates a higher price (a longer lead-time) than the customer is willing to accept, which results in a sharp decrease in demand and a high profit loss. When b is overestimated, the offered price is lower than the customer is willing to pay, and the generated demand becomes higher than optimal, which also results in lower profits. Although a similar reasoning follows for c, we observe that large overestimation errors result in higher profit losses than underestimation. As capacity increases, the gap between the decentralized and centralized solutions decreases and the contract becomes more robust to estimation errors in b. Interestingly, we observe the highest profit loss at medium capacity levels for c as compared to low and high capacities, since there is more room to make errors at medium capacity levels, given the service level constraint. We finally note that *estimation errors in price sensitivity are much costlier than those in lead-time sensitivity*.



(i) **(ii)**

Figure 4: Percent Profit Loss when Price Sensitivity or Lead-time Sensitivity is misestimated

2.5 Capacity Decision

In this section, we include capacity as a decision variable, and compare the decentralized settings P, M and the centralized setting C. Let K denote the unit capacity cost. In the centralized setting, the firm aims to maximize profit, which is given by revenue minus production and capacity costs.

$$\max_{(\lambda_C, L_C, \mu_C) \geq 0} \quad \pi_c = (a - cL_c - \lambda_c)\lambda_c/b - m\lambda_c - K\mu_c$$
$$s.t. \quad (\mu_c - \lambda_c)L_c \geq k$$

As one unit of production will require at least one unit of capacity, the minimum cost incurred per unit will be $(m+K)$. Thus, we can revise Assumption A3 to $a-b(m+K)-ck/\mu > 0$, and constrain the capacity decision to $\mu_c > ck/(a-(m+K)b)$ in order to satisfy it. We also restrict our attention to values of $K \leq (a-mb)/b$ for non-triviality. In the decentralized setting P, where production is the leader, production first chooses a capacity and a lead-time and marketing then chooses a price. The best response of marketing to a given lead-time and capacity is given by Equation (5). The following proposition describes the optimal solution for C and P.

Proposition 10 *The optimal lead-time decisions under C and P are equal, i.e., $L_P^* = L_C^* = L$, and satisfy*

$$c^2L^3 - c(a - (m + K)b)L^2 + 2Kkb = 0 \tag{14}$$

(i) *for $K \leq \min(K^1, \bar{K})$ under C,*

(ii) *for $K \leq \min(K^0, \bar{K})$ under P,*

where K^1 and K^0 are the minimum values of K for which $\pi_C(L_C) = 0$ and $\pi_P(L_P) = 0$, respectively, and $\bar{K}$ is the K value beyond which Equation (14) does not have a real root on $\left[0, \frac{a-(m+K)b}{c}\right]$. Then, the optimal decisions will be given by

$$\lambda_C^*(L_C^*) = \frac{a - cL_C^*}{2} - \frac{(m + K)b}{2}, \quad p_C^*(L_C^*) = \frac{a - cL_C^*}{2b} + \frac{m + K}{2}, \quad \mu_C^* = \lambda_C^*(L_C^*) + \frac{k}{L_C^*} \tag{15}$$

$$\lambda_P^*(L_P^*) = \frac{a - cL_P^*}{2}, \quad p_P^*(L_P^*) = \frac{a - cL_P^*}{2b}, \quad \mu_P^* = \lambda_P^*(L_P^*) + \frac{k}{L_P^*} \tag{16}$$

Otherwise, capacity becomes too costly to generate positive profit.

It can be seen from Proposition 10 that the optimal capacity decision is given by the optimal generated demand plus an adjustment amount to meet the service level.

Corollary 1 *The difference in the optimal demand, capacity, price and profit between C and P is as follows: (i) $(\lambda_P^* - \lambda_C^*) = (\mu_P^* - \mu_C^*) = (m+K)b/2 > 0$ (ii) $p_C^* - p_P^* = (m+K)/2 > 0$ (iii) $\pi_C^* - \pi_P^* = (m + K)^2 b/4 > 0$.*

The inefficiencies caused by the decentralization of price, lead-time and capacity decisions can be clearly seen from Corollary 1. Although the lead-time decision is the same under both settings, there is no markup in price for the average cost per unit under the decentralized setting since marketing's performance is solely based on revenue. On the other hand, for the centralized setting, the markup is given by (m+K)/2. This discrepancy also results in an associated amount of extra demand and capacity under the decentralized setting, which lowers the profit.

In the decentralized setting M, production first chooses a capacity, and the rest of the game is exactly the same as the original marketing Stackelberg game. As a result of the analytical intractability of this problem, we compare the optimal decisions under different settings numerically. Figure 5 ($a = 50,\ b = 4,\ c = 4,\ s = 0.95,\ m = 5$) shows the optimal profit and decisions with respect to the capacity cost, K. We do not include P beyond the K value where positive profit cannot be generated. We can summarize our observations as

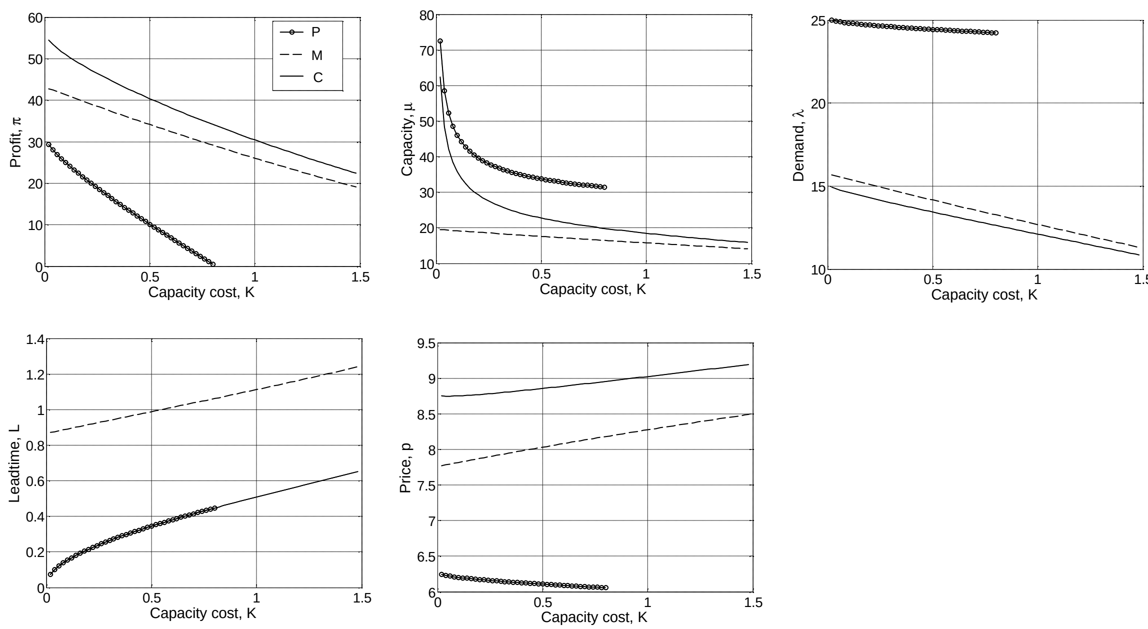


Figure 5: Comparison of Settings with Capacity Decision

follows:

- When capacity is included as a decision variable, the ordering of optimal decisions and profit under different settings is the same as in Proposition 4 at given capacity costs with the exception that $L_P^* = L_C^*$.

- The decentralized setting M prefers a lower capacity than the centralized setting, while the decentralized setting P prefers a higher one. This result is consistent with our previous findings, where M generated higher profits and was closer to C at low capacity levels. When marketing is the leader, a lower capacity is sufficient, while production needs to choose a high capacity to meet the generated demand as the leader, which becomes too costly beyond a certain point.

- When production is the leader, as K increases, capacity decreases and lead-time increases. Thus, marketing lowers price in response. When marketing is the leader, it responds to a lower capacity level with a higher price. Therefore, in Figure 5, we observe that as K increases, p^*_M increases while p^*_P decreases. Moreover, the profit generated under M approaches that under C, while the profit generated under P deviates.

2.6 Conclusion

We studied a firm with two independent functions, marketing and production, which serves customer demand that is sensitive to both price and lead-time. Price and lead-time decisions are made by marketing and production, respectively. Production needs to satisfy a certain percentage of orders on time under limited capacity. We analyzed the types of inefficiencies that result from the decentralization of these two functions.

In order to achieve coordination, we proposed a transfer price contract with bonus payments, where marketing pays production a transfer price per unit produced, and both departments receive a fraction of the total revenues generated as a bonus payment. We showed the existence of a unique transfer price for a given fraction of total revenues offered to marketing, α_1, that achieves coordination as long as production receives a satisfactory incentive as a fraction of total revenues. Finally, we analyzed the optimal decisions and profit when production can choose the capacity level.

Our key findings are as follows:

Decentralized Settings

- *Lead-times are longer, prices are lower, demand is larger and profits are lower as compared to the centralized setting.*
- *The lead-time decision is independent of the changes in price sensitivity or production cost as long as production receives a positive margin. In this case, the price decision is not affected by a change in the unit production cost.*
- *The unique production Stackelberg equilibrium is dominated by the unique marketing Stackelberg equilibrium. The dominance becomes more significant for firms having tight capacity.*
- *Higher capacity results in higher profits under the centralized setting and the decentralized setting, where production is the leader. However, higher capacity may result in a decrease of profits when marketing is the leader.*
- *When capacity can be chosen by production and has a constant unit cost, the dominance of the marketing Stackelberg game over the production Stackelberg game becomes more significant at higher capacity costs. As compared to the centralized setting, the optimal capacity level is higher when production is the leader and lower when marketing is the leader.*

Under Coordination:

- *Higher capacity does not necessarily lead to charging higher for better service.*
- *Under a Revenue-Sharing Contract, estimation errors in price sensitivity are much costlier than those in lead-time sensitivity when production is the leader. On the other hand, contract parameters are independent of the demand parameters when marketing is the leader.*

This research is to appear in IIE Transactions [97].

CHAPTER III

CENTRALIZED VS. DECENTRALIZED COMPETITION FOR PRICE AND LEAD-TIME SENSITIVE DEMAND

3.1 Introduction

Recent business trends and advances in consumer behavior modeling have shown that demand for goods and services, and in turn, profits of companies, are shaped by price and lead-time decisions. Quoting effective prices and reliable lead-times to match supply and demand is especially important as many companies are moving from a make-to-stock (MTS) to a make-to-order (MTO) model to reduce costs, increase profits, and improve market responsiveness [80, 131]. Customers look for a tailor-made product that precisely fits their needs, desires, and budgets and they want it delivered without waiting [89]. In fact, the ability to offer customized products with short lead-times is becoming an important area of competitive differentiation among suppliers in many industries [3]. Mike Eskew, the chairman and chief executive officer of UPS, explains: “Globalization has raised the competitive stakes, forcing companies to compete on more than just product features and price. Companies can achieve competitive differentiation based on how well they deliver the right product to the right place at the right time." [48].

Ideally, a firm should take a global perspective and coordinate its decisions on price and lead-time quotes for increased profitability. In reality, however, different divisions of large companies all too often fail to communicate on important business decisions [65, 28]. One of the reasons tied to the downfall of Silicon Graphics Inc. was its highly independent product divisions, which did not coordinate introduction schedules and led to stacked products on the manufacturing floor by the end of the year. When the salespeople’s assurance that products would ship on time lost credibility, customers started switching to competitor products [57].

In addition to communication failures, conflict can arise between the marketing and operations functions as a result of the internal compensation schemes. Nell Williams, Marriott's VP of Global Revenue Management Organization, points out for the hospitality industry: "Salespeople have historically been compensated on volume and not profit, and that's part of the reason why they are at odds with revenue managers. The whole hotel wins when both disciplines work together towards the same goal and that is bringing the most profitable business into the hotel." [136]. Similarly, in several manufacturing oriented firms, manufacturing is evaluated based on costs and operational efficiency while marketing is evaluated based on revenue and volume [6, 63]. From a consulting point of view, Yama *et al.* ([138]) discuss how frequently they come across the misalignment of a company's strategic goals and the pricing performance metrics that drive individual behavior, where the sales force is incentivized on order volume with no tie to profitability metrics. Similarly, Hogan and Nagle ([58]) and Preslan and Newmark ([104]) point out that the key to driving profitability is to compensate sales people based on profit contribution or margin and not just for sales volume or revenue.

In many firms, the division of functional responsibilities and conflicting incentives lead to decentralization of price and lead-time decisions, meaning that these decisions are made independently by separate agents with different objectives. Marketing quotes prices so as to maximize revenue, while manufacturing quotes lead-times so as to ensure reliable delivery given the production capacity and the incurred production costs. Clearly, a firm would benefit from coordinating decentralized decisions by setting the proper incentives. Several studies have noted performance improvements when marketing and manufacturing divisions work together [93, 78, 55]. However, there are very few studies that measure the impact of decentralization of price and lead-time decisions [74, 97].

We consider a duopoly where firms compete on the basis of their prices and uniform delivery time guarantees in a common market. In Chapter 2, we found that for a monopolistic firm, when price and lead-time decisions are decentralized, i.e., made by the marketing and production departments, respectively, lower prices and longer lead-times are quoted generating larger demand but lower profits as compared to a centralized structure in which prices and lead-times are quoted by a single decision maker. In this chapter, we extend that work to a competitive setting. We explore if and when decentralization can be more profitable than centralization under competition. We model this problem as a two-stage game, where in the first stage, firms simultaneously choose their organizational structures so as to operate in a centralized or decentralized fashion, and in the second stage, they simultaneously choose their price and lead-time decisions. Thus, we endogenize the strategic choice of being centralized or decentralized through the first stage, while we model the tactical price and lead-time competition in the second stage. When the outcome of the first stage is centralization for a firm, there is a single decision maker who determines the price and lead-time strategy. On the other hand, under decentralization, the strategy is established through a Stackelberg game, where marketing first sets the price as the leader and then production sets the lead-time as the follower, as the best response to competitor decisions. Once the price and lead-time strategies are determined, both firms simultaneously announce their price and lead-time decisions to the market, and subgame perfect equilibrium is reached when none of the firms has an incentive to unilaterally deviate from its decisions. We solve this problem through backwards induction; given the best response of each firm to its competitor's decisions under the organizational structure choice from the first stage, we solve the subgame perfect equilibrium in the second stage of the game. Afterwards, we determine the first stage choice of each firm comparing different decision making scenarios in terms of the price and lead-time decisions and firm profits: (i) both firms are centralized, (ii) a hybrid scenario where only one firm is centralized, (iii) both firms are decentralized.

We show the existence of a unique Nash Equilibrium under all scenarios through an iterative procedure, where each firm responds to a price or lead-time decrease (increase) by its competitor with a price and lead-time decrease (increase), and the game is played in a monotonically decreasing (increasing) fashion until equilibrium is reached. We find that under intense price competition, firms may suffer from a decentralized structure, particularly under high flexibility induced by high capacity, where revenue based sales incentives motivate sales/marketing for more aggressive price cuts resulting in eroding margins. Fierce price competition has been observed in several markets, where firms cut prices aggressively in response to competition. For example, Unilever suffered from fierce price competition in European supermarkets against other household and personal care suppliers such as Procter & Gamble as well as suppliers in other grocery categories, which resulted in eroding margins [88].

We find that *when price competition is more intense than lead-time competition*, where the intensity is characterized by the underlying parameters of market demand, the net effect of lower prices and longer lead-times under a decentralized structure is a decrease in the potential market demand of the competitor that drives prices downward, hurting the profits of both firms in the market. Nagle and Hogan ([90]) discuss that fierce price competition may be more appropriate for low cost firms. We find that low cost firms may benefit from a decentralized structure without hurting margins. However, although a decentralized structure may generate higher market share, it may not account for the decrease in margins as the costs get higher. Particularly, losses may be significant for high capacity firms, where marketing will be more aggressive in pricing to generate more demand. Therefore, a centralized structure becomes crucial for more profitable use of capacity, leading to shorter lead-times as a competitive advantage. For example, the threat of competition from low cost overseas manufacturers, particularly China, has been an ongoing concern for American manufacturers. Chinese manufacturers offer low prices, while domestic manufacturers can offer shorter delivery times. For the metal parts industry, intense global competition has hindered domestic producers from increasing their prices, and motivated them for shortening lead-times to improve competitiveness [119]. Similarly, the CEO of American Leather, Bob Duncan, discusses that although it is not possible to beat the Chinese furniture makers on price, no Chinese furniture maker can deliver a sofa in four weeks: “The fact that you’re across the ocean is adding a month to your lead time almost by definition... What I’m most proud of is the fact that we still do ship in two to three weeks" [103]. Thus, a centralized organizational structure becomes important for domestic manufacturers to offer a shorter lead-time at the expense of higher prices instead of going into aggressive price cuts.

In contrast, we find that *when price competition in the market is less intense than lead-time competition*, a decentralized organizational structure may dominate a centralized one. For example, a firm may choose to compete against the low prices of a higher capacity firm with a decentralized structure to maximize its market share. Finally, a firm with an increased advantage over price competition, where customers are less sensitive to its prices in comparison to competition, can also benefit from a decentralized structure.

This chapter is organized as follows. In Section 3.2, we provide a review of the literature on price and lead-time competition. In Section 3.3, we introduce our model and assumptions. We describe the best response of a firm, given its competitor’s price and lead-time decisions for both the centralized and decentralized structures, and the equilibrium solution for the duopoly problem in Section 3.4. In Section 3.5, we describe the first stage equilibrium solution through the comparison of different decision making scenarios. We also discuss the effect of capacity and production cost on the price and lead-time competition in the market. After analyzing some special cases, namely, unconstrained price competition and lead-time only competition for analytical insights in Section 3.6, we provide our conclusions in Section 3.7.

3.2 Literature Review

Most of the previous research on price and lead-time decisions in a competitive steady-state setting uses queueing models and considers centralized firms. Several researchers model lead-time decisions via a “waiting time standard" as determined by the time spent in a queue given the allocated capacity. Instead of modeling customers' sensitivity to price and lead-time independently, some researchers aggregate price and waiting time into a "full price". Loch ([75]) and Armony and Haviv ([5]) study two competing service providers operating as M/G/1 in the former and M/M/1 in the latter, and two customer classes, where each class has a given waiting cost rate and chooses a provider based on its full price. In the latter study, competition is modeled in two stages such that providers compete on the basis of service charges in the first stage, and customer classes compete with allocation decisions in the second stage. Chen and Wan ([29]) study two M/M/1 service providers that compete for a single customer class on the basis of full price, but charge the same full price in the long run. Providers are differentiated by their capacities, values of service and unit costs of waiting. Lederer and Li ([71]) consider N M/G/1 service providers, which compete for N customer classes by choosing prices, production rates and scheduling policies. They assume that providers are full price takers. While capacity is treated as constant in these studies, Cachon and Harker ([24]) present the option of outsourcing to a supplier for two competing firms, which experience scale economies as their unit costs are decreasing in the demand volume. Two types of competition are analyzed: an M/M/1 queueing game with price and time sensitive demand and an EOQ game with fixed ordering costs and price sensitive demand. For the queueing game, each firm's demand rate is modeled as a function of the full prices of both firms with two forms: linear and truncated logit.

In contrast to the full price approach of the first set of papers, Allon and Federgruen ([1, 2]) treat price and waiting time as independent factors in customer demand, which decreases in own-price/time effects, increases in cross-price/time effects and accounts for other factors such as brand in the intercept. Both papers model N M/M/1 firms, the former for a single customer class and the latter for N customer classes. In [1], rather than using waiting time as is in the demand model, the authors use service level, which is defined as the difference between an upper bound benchmark for waiting time and the firm's actual waiting time standard, and expressed in terms of the expected waiting time or the ϕ fractile of the waiting time distribution. A cost per unit time proportional to adopted capacity is included in the profit function. Three types of competition are studied: Two-stage games, where service level is set in the first stage while price is set in the second stage and vice versa, and simultaneous price and service competition. In [2], waiting time is explicitly incorporated into the demand model. A class dependent cost and a cost per unit time proportional to capacity are included in the profit function. Price only competition, waiting time only competition, and simultaneous competition are studied using dedicated or shared facilities for customer classes.

Along the same line of research, So ([113]) extends the work of [114] to a competitive setting of N M/M/1 firms using a multiplicative competitive interaction model, where the market size is constant and shared among firms based on their “attraction" given their quoted prices and lead-times. Moreover, each firm needs to meet a predetermined service level so as to satisfy a certain percentage of the orders on time. Boyaci and Ray ([21]) also use a service level constraint to study two substitutable products, which are differentiated in the quoted prices and lead-times and served by dedicated capacities in an M/M/1 firm. However, in this case, the objective is to maximize the overall profit generated from both products. Tsay and Agrawal ([123]) study a distribution system, where a manufacturer supplies a common product to two retailers who use price and service quality (effort) to directly compete for end customers in a deterministic setting.

Some researchers model duopolies, where customers strategically choose the firm that maximizes their expected utilities. In [72], the utility function is based on price, quality and response time. Customers can observe the congestion levels of the firms, may jockey from one queue to another and their choices are dynamic. Besbes and Zeevi ([14]) model utility as a function of price and waiting time, where price is the only decision variable. Their focus is on the effect of uncertainty in model demand parameters on the decisions and the competition. Ho and Zheng ([56]) consider a lead-time only utility model, where customers are sensitive to quoted lead-time and service quality, which is defined as the difference between the quoted lead-time and customer expectation. The objective of each firm is to maximize its demand rate.

All of the papers discussed above study competition among centralized firms. Papers that study competition among decentralized firms mainly focus on price and/or quantity decisions. Bhardwaj ([15]) and Mishra and Prasad ([85]) consider the problem of delegating pricing decisions to the salesforce in a duopoly within a principal agent framework. The demand for each firm is modeled as a function of the prices and the salesperson effort levels of both firms. Parlar and Weng ([96]) consider a single period model for the price decision faced by the marketing department and the production quantity decision faced by the production department. They allow the two departments to coordinate their decisions to compete against another firm with a similar organizational structure for price sensitive demand. They compare the results under marketing - production coordination and no coordination. In [83] and [20], the focus is on two supply chains, which consist of a wholesaler/manufacturer and a retailer, and compete on the basis of price in the former and customer service, namely fill rate, in the latter. McGuire and Staelin ([83]) use a deterministic framework, while Boyaci and Gallego ([20]) use a queueing model with generic lead-time distribution. Three scenarios are analyzed: 1) Both supply chains are uncoordinated, i.e., each party selects their own decisions (prices in [83] and service and inventory levels in [20]), 2) a hybrid scenario where only one supply chain is coordinated, and 3) both supply chains are coordinated. Bernstein and Federgruen ([9]) study a similar multi-period setting as in [8], where there exist a common supplier and competing independent retailers. Customer demand depends on all of the firms' prices and a measure of service level, namely fill rate, and is modeled in three forms: (i) Attraction type multinomial logit (ii) linear model with own and cross effects (iii) log separable. They consider price competition only as well as simultaneous price and service competition and develop coordination mechanisms. Finally, Balasubramanian and Bhardwaj ([6]) model a duopoly in which firms with decentralized marketing and manufacturing functions with conflicting objectives compete on the basis of price and quality in a deterministic setting. To the best of our knowledge, our work is the first to study centralized and *decentralized* decision making comparatively under price and lead-time *competition* in a steady state setting.

3.3 Model Assumptions

We consider two competing firms in a MTO setting. Capacity is assumed to be constant, while price and lead-time are decision variables. Firm operations are modeled as an M/M/1 queue. We use the following notation throughout the text:

Parameters: $(i, j \in \{1, 2\})$

a_i : base market potential for firm i (maximum attainable demand under no cross-effects)

b_i : own price sensitivity of demand for firm i

c_i : own lead-time sensitivity of demand for firm i

β_{ij} : cross price sensitivity of demand for firm i, $j \neq i$

γ_{ij} : cross lead-time sensitivity of demand for firm i, $j \neq i$

m_i : unit production cost of firm i

μ_i : capacity of the production system (service rate) of firm i

s_i : service level (the minimum probability of meeting the quoted lead-time) for firm i

k_i : used for computational simplicity, $k_i = \ln(1/(1 - s_i))$

Decision Variables

S_i : Organizational structure decision of firm $i = 1, 2$ (C for centralized and D for decentralized)

p_i : price quoted by the marketing department of firm i ($p_i \geq m_i$)

L_i : lead-time quoted by the production department of firm i ($L_i \in [0, k_i/\mu_i]$)

λ_i : mean demand rate for firm i

π_i : profit achieved by firm i

π_i^M, π_i^P : profit achieved by the marketing and production departments, respectively, of firm i

If the two firms are identical, i.e., have the same parameter values, we drop the firm-specific subscripts i, j. Our demand model is given by:

$$\lambda_i = a_i - b_i p_i - c_i L_i + \beta_{ij} p_j + \gamma_{ij} L_j \quad j = 3 - i,\ i = 1, 2 \tag{17}$$

Equation (17) is linear in the quoted price and lead-time and cross price and cross lead-time effects, which is similar to the demand models used in [123, 21, 6]. However, we do not require the base market potentials, a_i, or other demand parameters of the firms to be equal, generalizing earlier models. In that respect, our demand model is closest to the one used in [1], where we use a linear form of their general concave waiting time function with an intercept, i.e., the base market potential, and no explicit upper bound for the waiting time standard. However, note that the research problems in the two papers are different. [1] use the ϕ fractile of the waiting time distribution, which would correspond to our service level s, to determine the capacity required and they incorporate it into the profit function of each firm via a linear capacity cost. On the other hand, we choose what lead-time to quote given the level of capacity and the required service level. In Section 3.4.1, we show that the service level constraint is tight at optimality. Thus, for a specific capacity cost, our centralized model may generate the same solution as in their model, although different results may be obtained under different cost levels. Moreover, our focus is on the comparison of centralized and decentralized decision making, while they do not consider the decentralization of price and waiting time decisions.

In [21, 123], the total market size is decreasing in the quoted price and lead-time (service in the latter) of both firms but is independent of cross-effects, while in [6] the total market size is constant. As we allow demand parameters to vary between the two firms, the total market size in our model is not constant:

$$\lambda_1 + \lambda_2 = (a_1 + a_2) - (b_1 - \beta_{21})p_1 - (b_2 - \beta_{12})p_2 - (c_1 - \gamma_{21})L_1 - (c_2 - \gamma_{12})L_2 \tag{18}$$

One unit decrease in the price of Firm 1, p_1, results in an increase of b_1 customers (units of demand) for Firm 1 of which β_{21} customers switch from Firm 2. Thus, the "new" customers that Firm 1 gains is given by $b_1 - \beta_{21}$. Note that, everything else being constant, one unit of decrease in the price of Firm 1 steals β_{21} customers from Firm 2, while one unit of decrease in the price of Firm 2 steals β_{12} customers from Firm 1. The difference in β_{12} and β_{21} would be determined by other attraction factors, such as brand, loyalty or location. We make the following assumptions[1]:

A1. There is a unit production cost, m_i, for each firm ($i = 1, 2$).

A2. All parameters are positive and common knowledge to both parties:

$$a_i > 0,\ b_i > 0,\ c_i > 0,\ \beta_{ij} > 0,\ \gamma_{ij} > 0,\ m_i > 0,\ \mu_i > 0,\ 0 < s_i < 1 \quad j = 3-i,\ i = 1, 2$$

A3. $b_i > \beta_{ji},\ c_i > \gamma_{ji} \quad (i, j \in \{1, 2\},\ j \neq i)$

A unit increase (decrease) in the price/lead-time quoted by a firm creates a larger decrease (increase) in its own demand than an increase (decrease) in its competitor's demand. This assumption also ensures that the total market size is decreasing in the price and lead-time of both firms.

A4. $b_i > \beta_{ij},\ c_i > \gamma_{ij} \quad (i, j \in \{1, 2\},\ j \neq i)$

The demand generated by a firm is affected more by a unit change in its own price/lead-time than by a unit change in its competitor's price/lead-time.

A5. (Positive Demand Assumption) There is positive demand for each firm in its base market to provide its services when the smallest reasonable price, (m_i), and the shortest lead-time that satisfies its service level constraint, (k_i/μ_i), are chosen:

$$\lambda_i = a_i - b_i m_i - c_i k_i/\mu_i > 0 \quad j = 3 - i,\ i = 1, 2$$

This assumption is a sufficient but not necessary condition for the existence of a competitive equilibrium in the market, i.e., a competitive equilibrium might exist

[1] Assumptions A3 and A4 are also used in [1] for the price terms.

even if the condition of the assumption is not satisfied. However, if a profitable equilibrium solution does not exist for either firm, one or both of the firms may need to leave the market. Note that it is not unrealistic to expect that a firm should be able to generate some demand in its base market even if a competitor does not exist. In other words, a firm cannot continue to exist in the long run only through attracting customers from its competitor's base market. This assumption also facilitates the derivation of some results through the paper.

Next, we describe our game structure, which consists of two stages. In the first stage, both firms simultaneously choose an organizational structure so as to operate centralized or decentralized for making price and lead-time decisions. Thus, the outcome of the first stage is the pair of strategic decisions (S_i^*, S_j^*) for firms $(i, j) \in (1, 2)$, which is observed by both firms. In the second stage of the game, we model the tactical price and lead-time competition. If the outcome of the first stage is centralization for a firm, then there is a single decision maker who chooses the price and lead-time strategy for the firm. On the other hand, if the outcome of the first stage is decentralization (say for firm i), the strategy is established through a Stackelberg game, where the marketing department chooses a price, $p_{i(D,S_j^*)}$, as the leader and then, the production department chooses a lead-time, $L_{i(D,S_j^*)}(p_{i(D,S_j^*)})$, as the follower. Note that we use subscripts to denote organizational structures to differentiate between strategic and tactical decisions. Once the strategies are determined, both firms simultaneously announce their price and lead-time decisions to the market, and the market demand for each firm is realized. The subgame perfect equilibrium is reached when none of the firms has an incentive to unilaterally deviate from its decisions. Figure 6 demonstrates the sequence of events under each organizational structure for both firms.

Note that this decentralized game framework is different from the one in [83] and [20], where competition occurs in two stages; retail competition preceded by manufacturer competition with manufacturer as the Stackelberg leader. As we model marketing and production as functions of the same firm, we consider one unified stage of competition after prices

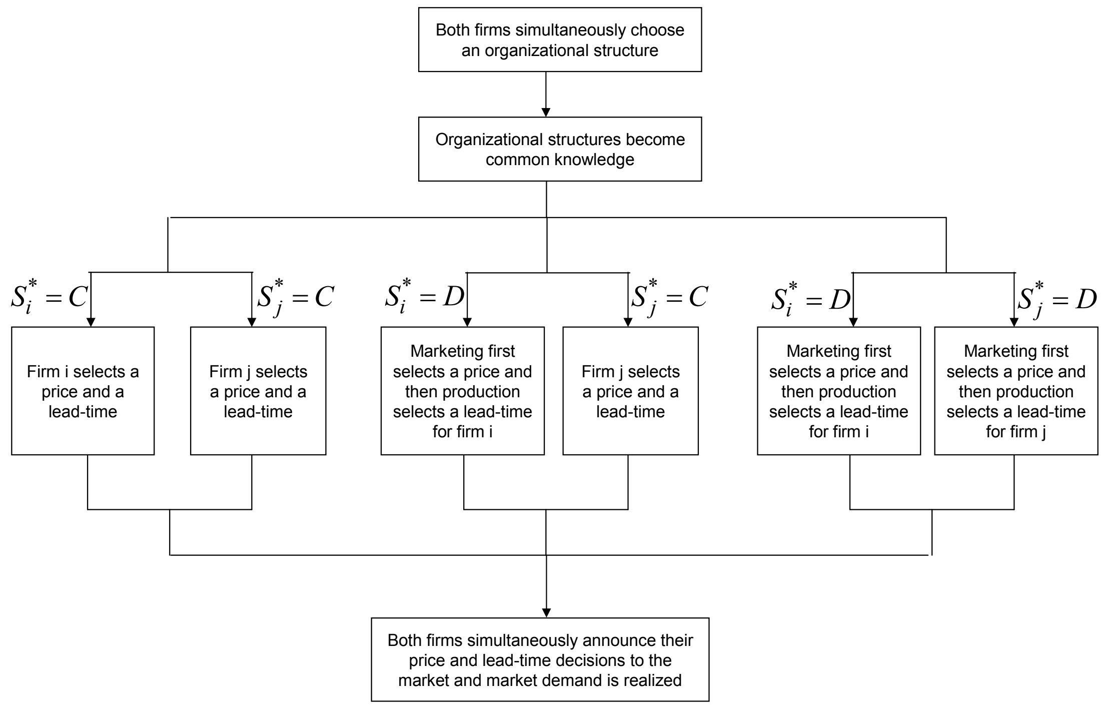


Figure 6: Sequence of Events for the Two-Stage Game

and lead-times are determined within each firm in a Stackelberg framework with marketing as the leader. We assume that both firms are rational players with common knowledge of the problem parameters, and the divisions within the firms employ sequential rationality in case of decentralization.

3.4 Stage 2 - Tactical Price and Lead-time Competition

For this stage, we first describe Firm i's best response to its competitor's decisions under both centralized and decentralized structures. We then demonstrate the equilibrium solution under competition.

3.4.1 Firm i Problem

We first analyze the optimization problem for firm i ($i = 1, 2$) as a best response to the price and lead-time decisions of firm $j \neq i$, $(p_{j(S_i^*, S_j^*)}, L_{j(S_i^*, S_j^*)})$, given the strategic outcomes from stage 1 (S_i^*, S_j^*). Let $\hat{J}$ denote firm j decisions $(S_j^*, p_{j(S_i^*, S_j^*)}, L_{j(S_i^*, S_j^*)})$. If $S_i^* = C$, there is a single decision maker who chooses the price and lead-time decisions with the objective of maximizing firm profit:

$$\max_{p_{i(C,\hat{J})} \geq m_i \ , \ L_{i(C,\hat{J})} \geq 0} \left(p_{i(C,\hat{J})} - m_i\right) \lambda_{i(C,\hat{J})} \quad \text{s.t.} \quad \left(\mu_i - \lambda_{i,(C\hat{J})}\right) L_{i(C,\hat{J})} \geq k_i$$

If $S_i^* = D$, we assume that marketing's performance is evaluated as a revenue center. Thus, first, marketing makes a price decision to maximize firm revenue, and its problem is:

$$\max_{p_{i(D,\hat{J})} \geq m_i} p_{i(D,\hat{J})} \lambda_{i(D,\hat{J})} \tag{19}$$

Then, production makes a lead-time decision as its best response to this price decision given its own objective. We assume that production is evaluated as a cost center. Giving $p_{i(D,\hat{J})}$ as an incentive for generating positive demand, production's objective becomes maximizing firm profit:

$$\max_{L_{i(D,\hat{J})}(p_{i(D,\hat{J})}) \geq 0} \left(p_{i(D,\hat{J})} - m_i\right) \lambda_{i(D,\hat{J})} \quad \text{s.t.} \quad \left(\mu_i - \lambda_{i(D,\hat{J})}\right) L_{i(D,\hat{J})}(p_{i(D,\hat{J})}) \geq k_i \tag{20}$$

Note that as $p_{j\cdot}$ and $L_{j\cdot}$ are given, we can redefine the market potential for firm i under both organizational structures as $A_i = a_i + \beta_{ij} p_{j\cdot} + \gamma_{ij} L_{j\cdot}$, which we refer to as the "derived market potential". Then, the generated demand becomes $\lambda_{i\cdot} = A_i - b_i p_{i\cdot} - c_i L_{i\cdot}$, which reduces firm i problem to the monopolistic firm problem in Chapter 2. All proofs can be found in the appendix.

Proposition 11 *Given* $(p_{j(S_i^*, S_j^*)}, L_{j(S_i^*, S_j^*)})$*, the optimal demand generated by firm i under the centralized organizational structure,* $\lambda^*_{i(C,\hat{J})}$*, is given by the unique root of* $f_{i(C,\hat{J})}(\lambda_{i(C,\hat{J})})$ *on the interval* $[0, \mu_i]$*, where*

$$f_{i(C,\hat{J})}(\lambda_{i(C,\hat{J})}) = (A_i - 2\lambda_{i(C,\hat{J})} - m_i b_i)(\mu_i - \lambda_{i(C,\hat{J})})^2 - c_i k_i \mu_i \tag{21}$$

Under the decentralized organizational structure, the optimal demand generated by firm i is given by $\lambda^*_{i(D,\hat{J})} = \min\{\lambda^0_{i(D,\hat{J})}, \bar{\lambda}\}$*, where* $\bar{\lambda} = \frac{A_i - b_i m_i + \mu_i - \sqrt{(A_i - b_i m_i - \mu_i)^2 + 4 c_i k_i}}{2}$ *and* $\lambda^0_{i(D,\hat{J})}$ *is the unique root of* $f_{i(D,\hat{J})}(\lambda_{i(D,\hat{J})})$ *on the interval* $[0, \mu_i]$*, where*

$$f_{i(D,\hat{J})}(\lambda_{i(D,\hat{J})}) = (A_i - 2\lambda_{i(D,\hat{J})})(\mu_i - \lambda_{i(D,\hat{J})})^2 - c_i k_i \mu_i \tag{22}$$

The optimal lead-time and price under both organizational structures are then given by

$$L^*_{i\cdot}(\lambda^*_{i\cdot}) = \frac{k_i}{\mu_i - \lambda^*_{i\cdot}} \qquad\qquad p^*_{i\cdot}(\lambda^*_{i\cdot}) = \frac{A_i - \lambda^*_{i\cdot} - c_i L^*_{i\cdot}(\lambda^*_{i\cdot})}{b_i} \tag{23}$$

Note that the best response of firm i under a decentralized structure results in lower prices and longer lead-times as compared to a centralized structure similar to Chapter 2.

Observation 5 *The optimal prices, lead-times, generated demand and the optimal profit for firm i under the centralized and decentralized organizational structures increase in $p_{j\cdot}$, $L_{j\cdot}$, β_{ij} and γ_{ij}.*[2]

This observation directly follows from the monopolistic firm results in Chapter 2, where it is shown that the optimal decisions and the firm profit increase in the market potential. An increase in the sensitivity of firm i's customers to its competitor's prices/lead-times and/or a direct increase in its competitor's quoted prices/lead-times results in an increase in firm i's demand as more customers switch from firm j to firm i. Thus, the quoted lead-time and price increase. (Alternatively, when its competitor cuts its prices or lead-times, firm i answers with a price and lead-time decrease.). Price cutting in response to competition has been observed in several industries. In 2002, after Sony announced that it would cut the price of its PlayStation 2 game console from \$299 to \$199, Microsoft matched Sony's markdown the next day for its Xbox console at E3, which was followed by Nintendo's response of reducing the price of its GameCube platform from \$149 to \$50 [107]. Similarly, in 2004, Wal-Mart's price cut in its standard DVD rentals-by-mail plan by 7.5% was followed by similar price cuts in the plans of its competitors, Netflix and Blockbuster [18]. In order to gain a competitive advantage, companies have also strived to improve their processes to cut their lead-times/service times. For example, the big three of the U.S. automobile industry (Chrysler, Ford and General Motors) reduced their lead-times from 61

[2] *Note that under the decentralized organizational structure, if $\lambda^*_{i(D,\hat{J})} = \bar{\lambda}$, i.e., $p^*_{i(D,\hat{J})} = m_i$, for a given range of A_i, then optimal lead-times and generated demand still increase in competitor decisions and cross sensitivities. However, the optimal price and profit are not affected within this range of A_i.*

months to 52 months in order to compete against the low lead-times of Japanese manufacturers [49].

Note that although [113] uses an attraction type demand model, Observation 5 is consistent with his findings. As the “attractiveness" of its competitor increases, i.e., a decrease in the $\beta_{ij}p_{j\cdot} + \gamma_{ij}L_{j\cdot}$ term for our model, firm i needs to compete with a lower price and lead-time.

3.4.2 Duopoly Problem

Under competition, both firms simultaneously announce their price and lead-time decisions to the market. Equilibrium is reached when none of the firms has an incentive to unilaterally deviate from its decisions. The equilibrium solution is given by the simultaneous solution of the price and lead-time equations for $i = 1, 2$ for the related organizational structures in Proposition 11. As these equations do not have a closed-form solution, to draw insights about the equilibrium decisions and profits, we solve this subgame using an iterative procedure, similar to the one in [113], where the game is repeatedly played starting at an initial solution until the subgame perfect Nash equilibrium is reached. Note that this procedure is also generalizable to the N-firm problem. We present the procedure only for two firms under centralized and decentralized organizational structures:

Iterative Procedure for Computing the Nash Equilibrium:

1. (Initialization) Set $p_{i(S_i^*,S_j^*)} = m_i$ and $L_{i(S_i^*,S_j^*)} = k_i/\mu_i$ for $i = 1, 2$.

2. (Iterative Step) Without loss of generality, start with firm $i = 1$. Calculate the best response of firm i, $p_{i(S_i^*,S_j^*)}$ and $L_{i(S_i^*,S_j^*)}$, as given by the solution of Equations (21) and (23) for $S_i^* = C$, and of Equations (22) and (23) for $S_i^* = D$ using the current values of $p_{j(S_i^*,S_j^*)}$ and $L_{j(S_i^*,S_j^*)}$ for firm $j = 3-i$. Update the values of $p_{i(S_i^*,S_j^*)}$ and $L_{i(S_i^*,S_j^*)}$. Repeat this for i=2.

3. (Convergence criteria) Repeat Step (2) until the profits of both firms differ from their previous values by less than a predetermined tolerance level ϵ.

Proposition 12 *The iterative procedure described above converges to the unique subgame perfect Nash equilibrium for the simultaneous price and lead-time competition game given the outcomes from the first stage* (S_i^*, S_j^*).

Given that prices and lead-times are bounded below and above, when the game is iteratively played, the optimal decisions and profits monotonically increase or decrease (depending on the starting point) for both firms converging to the unique subgame perfect Nash Equilibrium.

3.5 Stage 1 - Strategic Decisions for Organizational Structure

Having identified the subgame perfect equilibrium for the second stage, we now discuss how each firm would choose an organizational structure. We first discuss the case of identical firms.

3.5.1 Identical Firms

In order to identify the equilibrium outcome of the first stage, we compare the profits generated under the four possible outcomes of this stage, which we hereafter refer to as scenarios: $(S_1^*, S_2^*) = (C, C)$, $(S_1^*, S_2^*) = (C, D)$, $(S_1^*, S_2^*) = (D, C)$ and $(S_1^*, S_2^*) = (D, D)$. We use $\succ$ to represent the dominance of one scenario over the other with a scenario subscript of 12 indicating dominance for both firms. The following proposition compares the second stage equilibrium decisions for each scenario.

Proposition 13 *For identical firms, the subgame perfect Nash Equilibrium solution for the second stage is symmetric under* (C, C) *and* (D, D)*. As compared to scenario* (C, C)*, the lead-time quoted under* (D, D) *is longer, the price is lower and the demand generated is larger. On the other hand, under a hybrid scenario, the centralized firm quotes higher prices and lower lead-times than the decentralized firm, which leads to lower demand and not always higher profits.*

We demonstrate the second part of Proposition 13 with the following example in Table 2. The first point to note from Table 2 is the significant decrease in profits when β (cross-price

Table 2: Equilibrium Decisions and Profits under (C, D) for Identical Firms.

	Firm 1 (C)				**Firm 2 (D)**			
β	$L^*_{1(C,D)}$	$p^*_{1(C,D)}$	$\lambda^*_{1(C,D)}$	$\pi^*_{1(C,D)}$	$L^*_{2(C,D)}$	$p^*_{2(C,D)}$	$\lambda^*_{2(C,D)}$	$\pi^*_{2(C,D)}$
3	0.252	32.214	63.108	1080.007	0.741	30.743	70.957	1109.984
2	0.086	25.198	40.001	403.933	0.395	20.370	67.420	355.318

$(a = 100,\ b = 4,\ c = 4,\ m = 15.1,\ s = 0.95, \mu = 75, \gamma = 1.)$

sensitivity) decreases. It follows from Observation 5 that under a lower β, the best response decisions of firm i to firm j are lower, which in turn, results in a decrease in its competitor's best response decisions and profit. Following the logic from the iterative procedure, when we re-start the game from this point onwards, the optimal decisions and profits will be monotonically decreasing at each iteration until the equilibrium is reached. Thus, we observe lower profits under a lower β. Conversely, we can explain this phenomenon as follows. When the intensity of price competition (β/b) increases, the number of customers lost through “net own" effects $((b-\beta)/b)$ decreases. It can be seen from Equation (18) that the total market size is decreasing in the quoted price of each firm by a factor of $b - \beta$. Both firms desire to capture as much demand as possible from the total market potential $(2a)$ to maximize profit (revenue) in a centralized (decentralized) organizational structure. Thus, as β increases, $b-\beta$ decreases and each firm can charge higher prices. Furthermore, as more customers switch between the two firms but fewer customers leave the market, the generated demand by both firms increases. Thus, profits increase in β.

We also observe that the centralized firm generates higher profits than the decentralized firm when $\beta = 2$, while the opposite is true when $\beta = 3$. Under both cases, the centralized firm prices higher than the decentralized firm, which puts the decentralized firm at an advantage[3]. However, when the intensity of price competition decreases, “net own" effects

[3]Although the decentralized firm quotes a longer lead-time than the centralized firm, the effect of lead-times on the generated demand is smaller than the effect of prices, as lead-times are already short under high capacity and the cross lead-time sensitivity is low.

become more significant and quoted prices decrease as explained above. As the capacity is high and flexible, the decentralized firm makes a more aggressive price decrease than the centralized firm, which generates a larger demand but lower profits given its lower margin. One should also note for this example that both firms would be better off under scenario (C,C), where each firm would achieve a profit of 1211.509 at $\beta = 3$ and 539.054 at $\beta = 2$.

Proposition 14 *When* $\frac{\beta}{b} \geq \frac{\gamma}{c}$, $(C,C)_{12} \succ [(C,D),(D,C)]_{12} \succ (D,D)_{12}$ *holds, and* $(S_1^*, S_2^*) = (C,C)$ *is the unique Nash equilibrium solution for the first stage game.*

Proposition 14 states that when the percentage of customers lost through price competition (with respect to the total number of customers lost through own price effects) is greater than that lost through lead-time competition, both firms are better off under (C,C) than under a hybrid scenario and worse off under (D,D). We can also interpret this result as in the following observation.

Observation 6 *When price competition is more intense than lead-time competition in the market, a centralized organizational structure is dominant for both firms.*

The best response of firm i to its competitor's decisions is lower prices and longer lead-times under a decentralized organizational structure as compared to a centralized one. When price competition is more intense than lead-time competition, the net effect of this price decrease and lead-time increase is a decrease in the derived market potential of the competitor, which results in lower prices, lead-times, demand and profits for the competitor. When we run the iterative procedure starting from this point, the game continues in a monotonically decreasing fashion for decisions and profits until convergence to equilibrium, and both firms end up with lower profits. Wanless ([133]) suggests that firms need to coordinate pricing decisions with operational decisions under intense price competition. Nagle and Hogan ([90]) discuss that matching any price cut without considering whether the cost is justified by the benefit can lead to a downward price spiral, where each competing firm cuts prices in response to one another until one stops, and it might be better to let the competitor have a price advantage at a high price than at a low one, which is consistent with our findings. Not only will each firm prefer to operate with a centralized structure but also will prefer its competitor to employ a centralized structure. Note that under a hybrid scenario, either firm may generate higher profits as we saw in the previous example.

3.5.1.1 Effect of Capacity

In this section, we analyze the effect of capacity on the competition and firm profits. In Figure 7, we demonstrate the change in the optimal profit of Firm 1 as capacity increases[4]. As the firms are identical, Firm 2 generates the same profits as Firm 1 under (C, C) and (D, D), while the profit curve of Firm 2 under (C, D) corresponds to the profit curve of Firm 1 under (D, C). Note that in this example, the decentralized firm in a hybrid scenario generates higher profits than the centralized firm since β is high as in the first example.

Observation 7 *Higher capacity does not always result in higher profits under competition even if it comes for free.*

In the monopolistic firm setting studied in Chapter 2, it was found that higher capacity led to higher flexibility and in turn, higher profits for a centralized firm. However, in a competitive setting, we observe that the profit generated under (C, C) increases up to a certain capacity level and then decreases. Thus, under competition, high capacity may increase the aggressiveness of competition as higher demand can be met and result in lower profits for both firms. This phenomenon is also observed in the industry. For example, Western Digital, one of the largest hard disk drive suppliers in the world, notes the following as a risk factor in their business: "... the hard disk drive market has experienced periods of excess capacity which can lead to liquidation of excess inventories and intense price competition. If intense price competition occurs, we may be forced to lower prices sooner and more than expected, which could result in lower revenue and gross margins." [135]. Note that a

[4]Parameter values are $a = 100,\ b = 4,\ c = 4,\ m = 15.1,\ s = 0.95,\ \beta = 3,\ \gamma = 1.$

similar result was also found in [113] for firms competing with a centralized organizational structure.

Observation 8 *A centralized organizational structure dominates under high capacity.*

This observation is consistent with the result in Chapter 2, which states that the gap between the centralized and decentralized structures increases under high capacity. However, we also observe that even if one firm employs a centralized structure under high capacity, it may suffer if its competitor employs a decentralized structure.

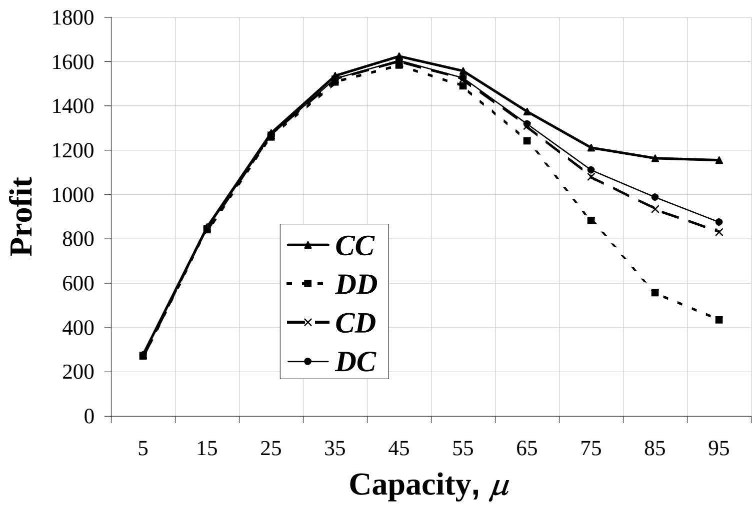


Figure 7: Profit vs. Capacity for Identical Firms.

3.5.1.2 Effect of Unit Production Cost

In this section, we analyze the effect of unit production cost for identical firms. In Figures 8 and 9, we provide a comparison of scenarios as measured in the percent profit increase over (C, C)[5]. Part (ii) in each figure uses a different scale and displays the dominant scenario at different cost levels. As we noted in the previous section, both firms generate the same profits under (C, C) and (D, D), and one firm's profit under (C, D) corresponds to the profit

[5]Parameter values for Figures 8 and Figures 9 are ($a = 100,\ b = 4,\ c = 4,\ \mu = 20,\ s = 0.95,\ \beta = 1,\ \gamma = 3.9$) and ($a = 100,\ b = 4,\ c = 4,\ \mu = 20,\ s = 0.95,\ \beta = 2.2,\ \gamma = 3.9$), respectively.

of the other under (D, C). We also choose parameters such that $\frac{\beta}{b} < \frac{\gamma}{c}$ and the production capacity is relatively tight.

In Figure 8, the intensity of price competition is low. Similar to our observations for capacity, we see that firms may lose significantly under a decentralized organizational structure, when the unit production cost is high as a result of eroding margins. Moreover, a centralized firm benefits more from competition if its competitor is decentralized. The gap between the centralized and decentralized firms in a hybrid scenario increases as the unit production cost increases. On the other hand, even when the operating costs are high, firms may benefit from a decentralized structure when the intensity of price competition is high as displayed in Figure 9. Note that under (D, D), the equilibrium decisions do not change with respect to the unit production cost, while the profits decrease as the margins decrease. Thus, in this case, we can argue that a centralized structure behaves over-protective of margins up until the unit production cost reaches around 19.

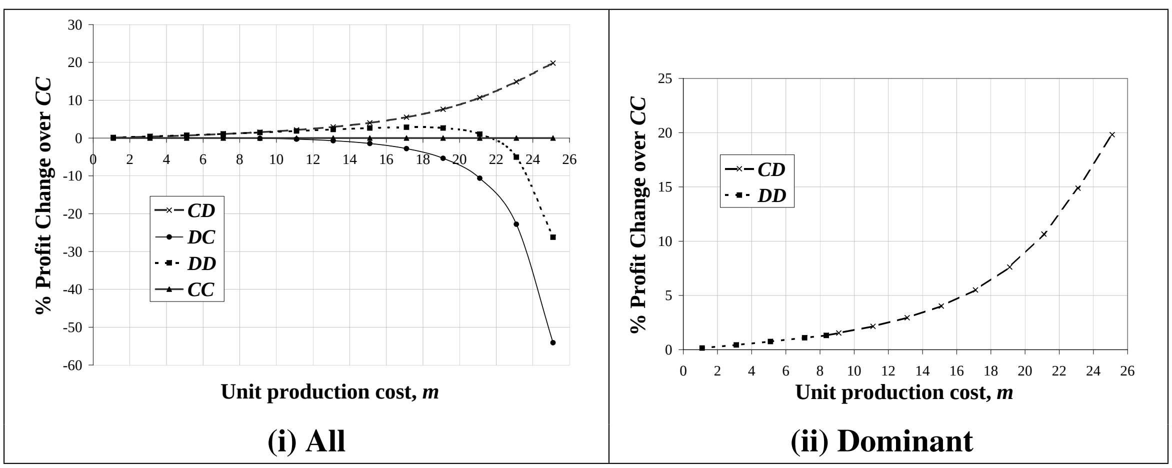


Figure 8: Comparison of Scenarios with respect to Unit Production Cost when the intensity of price competition is low ($\beta = 1$) (Identical Firms)

Figures 8 and 9 also show that as the unit production cost gets very low, the profit difference between the scenarios becomes insignificant, which is expected as the best response function under the centralized structure, Equation (21), approaches the one under the decentralized structure, Equation (22), as the unit production cost decreases. In fact, a margin

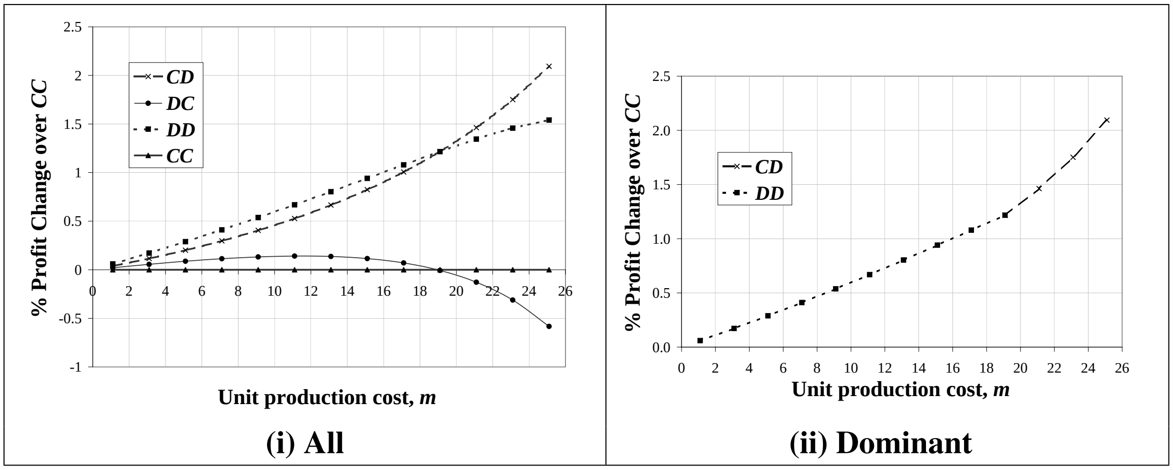


Figure 9: Comparison of Scenarios with respect to Unit Production Cost when the intensity of price competition is high ($\beta = 2.2$) (Identical Firms)

based incentive for marketing will generate the same best response function for both structures. Thus, even under high capacity or high production costs, firms may benefit from a decentralized organizational structure, where the incentive for marketing incorporates the margin and not just revenue. Michael V. Marn, a partner in McKinsey's Cleveland office, mentions that companies can be very successful with centralized or decentralized pricing. However, when they employ decentralized pricing, it is important to tie a higher level of incentives to the compensations of the salespeople [79]. Indeed, many firms are starting to employ price optimization software, where they can control pricing centrally specifying metrics such as revenue, volume and profit and leaving the execution to salespeople [79, 106].

3.5.2 Nonidentical Firms

In this section, we study the first stage equilibrium decisions for nonidentical firms, which do not necessarily have problem parameters as equal. We identify a similar condition as in the identical firm case for the dominance of the equilibrium outcome (C, C).

Proposition 15 *Under condition (24),* $(C,C)_{12} > [(C,D),(D,C)]_{12} > (D,D)_{12}$ *holds, and*

$(S_1^*, S_2^*) = (C, C)$ *is the unique Nash equilibrium solution of the first stage game.*

$$\frac{\beta_{12}}{b_2} \geq \frac{\gamma_{12}}{c_2} \text{ and } \frac{\beta_{21}}{b_1} \geq \frac{\gamma_{21}}{c_1} \tag{24}$$

Similar to the interpretation for Proposition 14, Proposition 15 states that when the percentage of customers lost through price competition (with respect to the total number of customers lost through own price effects) is greater for both firms than that lost through lead-time competition, a centralized organizational structure is dominant for both firms. We next consider condition (25):

$$\frac{\beta_{12}}{b_2} \geq \frac{\gamma_{12}}{c_2} \text{ and } \frac{\beta_{21}}{b_1} < \frac{\gamma_{21}}{c_1} \tag{25}$$

In other words, the percentage of customers that Firm 2 loses through price competition is higher than that by lead-time competition, while the opposite holds for Firm 1. We may observe this when Firm 2's reputation is based more on low prices, while Firm 1's reputation on speed of delivery, and thus, customers are more aware of competitor prices for Firm 2 and competitor lead-times for Firm 1. For example, in the express postal delivery industry, generally, FedEx has been perceived as the most time sensitive carrier in the business along with its successful tracking system, while the U.S. Postal Service (USPS) offers speed at a relatively low cost without the time guarantee and accurate tracking capability [118, 108]. Therefore, customers expect delivery speed and reliability from FedEx and low prices from the USPS, and are in general more sensitive to when their package is delivered by FedEx and what they pay for their delivery to USPS. In this respect, FedEx competes for time sensitive customers more intensely against UPS and DHL for which the USPS prices can be viewed as "the floor level [of pricing]" [7]. On the other hand, the USPS may face competition in price sensitive market segments through different products offered by these carriers. For example, catalog retailers who would trade delivery speed for lower rates were some of the biggest customers of the USPS "Parcel Select" service. UPS decided to target those price-sensitive large-volume shippers offering inexpensive products who do not need expedited or guaranteed delivery through its "UPS Basic" Service, which was soon followed by a similar service from FedEx [64, 76]. In our context, condition (25) could apply to FedEx as Firm 1 vs. the USPS as Firm 2 in express mail services, while the latter case of catalog retailers would correspond to a market, where price competition is in general more intense than lead-time competition, i.e., condition (24).

As price competition is more effective than lead-time competition for Firm 2 under condition (25), the net effect of lower prices and longer lead-times of Firm 2's decentralized structure is a decrease on the derived market potential of Firm 1. Thus, it holds that $(C,C)_{12} \succ (C,D)_{12}$ and $(D,C)_{12} \succ (D,D)_{12}$, as discussed in the proof of Proposition 15, and a centralized organizational structure is dominant for Firm 2. Similarly, if the net effect of Firm 1's decentralized structure on the derived market potential of Firm 2 is a decrease, $(C,C)_{12} \succ (D,C)_{12}$ and $(C,D)_{12} \succ (D,D)_{12}$ and a centralized structure is also dominant for Firm 1. On the other hand, if the net effect is positive, Firm 2 generates higher profits under (D,C) than (C,C) and under (D,D) than (C,D). We can observe this ordering of scenarios for Firm 2 in the example in Table 3. As the percentage of customers Firm 1 loses through lead-time competition is high, Firm 2 benefits from the longer lead-times quoted by a decentralized competitor and generates the highest profits under (D,C). On the other hand, for Firm 1, we observe that a centralized structure is dominant under $\beta_{12} = 2$, while a decentralized structure is dominant under a higher $\beta_{12} = 3.9$, which is consistent with our expectations based on the previous example. Under $\beta_{12} = 3.9$, the cross-price sensitivity of customers is much lower for Firm 1 than for Firm 2, and a unit price increase by Firm 2 results in a larger number of customers to switch to Firm 1 than vice versa. Thus, Firm 1 can not only charge prices higher than Firm 2, but it can also charge prices high enough such that a decentralized structure does not hurt margins. We can summarize our findings with the following observation.

Observation 9 *The firm with a competitive advantage over the quoted prices can benefit from a decentralized organizational structure in which case the competitor prefers a centralized structure.*

Table 3: Comparison of Scenarios for Non-identical Firms with Different Cross Sensitivities.

β_{12}	γ_{12}	**Firm 1**	**Firm 2**
2	1	$(C,C)_1 \succ (D,C)_1 \succ (C,D)_1 \succ (D,D)_1$	$(D,C)_2 \succ (C,C)_2 \succ (D,D)_2 \succ (C,D)_2$
3.9	1	$(D,C)_1 \succ (C,C)_1 \succ (D,D)_1 \succ (C,D)_1$	

($a = 100,\ b = 4,\ c = 4,\ m = 15.1,\ s = 0.95,\ \mu = 30,\ \beta_{21} = 2,\ \gamma_{21} = 3.$)

3.5.2.1 Effect of Capacity

In this section, we analyze the effect of capacity on the competition and firm profits. Particularly, we consider the effects of a capacity difference between the two firms with all other parameters being equal. In Figures 10 (i-ii) and 11 (i-ii), we provide a comparison of all scenarios for each firm as the capacity of Firm 1 changes, while Firm 2 has a fixed capacity ($\mu_2 = 25$)[6]. We display the dominant scenario right below each figure on a different scale for better visibility (Figures 10 (iii-iv) and 11 (iii-iv)). Instead of providing absolute profit figures, we measure the profit generated under each scenario in the percent profit increase over (C,C). Note that all the following examples have price competition less intense than lead-time competition ($\frac{\beta}{b} < \frac{\gamma}{c}$) so that we can explore cases, where a decentralized structure may be more profitable than a centralized structure.

Figure 10 represents a parameter setting, where the intensity of price competition is low ($\beta/b = 1/4$) and the significance of "net own" price effects is high ($(b-\beta)/b = 3/4$). Under this setting, both firms need to quote low prices to keep customers in the market and concentrate more on their own prices than competitor prices. As the intensity of lead-time competition is high ($\gamma/c = 3.9/4$), the firm with higher capacity will be able to use its competitive advantage through lower lead-times. Given that the significance of "net-own" price effects is high, both firms prefer a centralized structure regardless of the capacity level at Firm 1, which is consistent with our observations based on Table 2[7]. Similar to our

[6]Parameter values for Figures 10 and 11 are ($a = 100,\ b = 4,\ c = 4,\ m = 15.1,\ s = 0.95,\ \mu_2 = 25,\ \beta = 1,\ \gamma = 3.9$) and ($a = 100,\ b = 4,\ c = 4,\ m = 15.1,\ s = 0.95,\ \mu_2 = 25,\ \beta = 3,\ \gamma = 3.9$), respectively.

[7]$(C,C)_1 \succ (D,C)_1$ and $(C,D)_1 \succ (D,D)_1$ for Firm 1, and $(C,C)_2 \succ (C,D)_2$ and $(D,C)_2 \succ (D,D)_2$ for Firm 2.

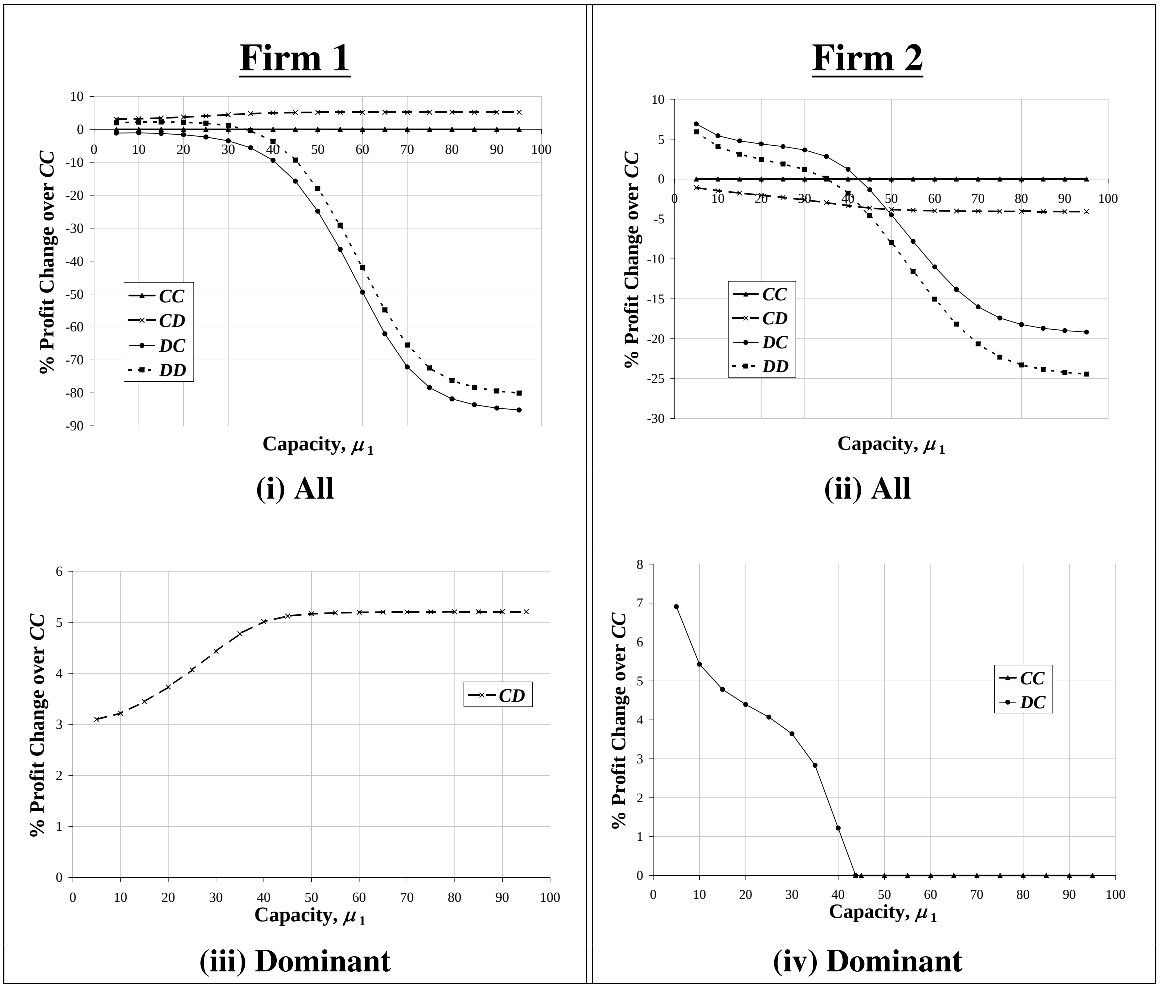


Figure 10: Comparison of Scenarios with respect to Firm 1 Capacity when the intensity of price competition is low ($\beta = 1$)

observations in the identical firm case (Figure 7), not only does Firm 1 lose significantly with a decentralized structure under high capacity, but it also harms its competitor (Figure 10 (i-ii)).

We also observe that (C, D) is the dominant scenario for Firm 1 at all capacity levels. As more capacity becomes available, Firm 1 prefers a centralized structure to make better use of the capacity. As the unit production cost is high, it is not able to cut prices aggressively. However, it prefers a decentralized competitor to use its competitive advantage through lead-times, as Firm 2 will quote longer lead-times with a decentralized structure than a centralized structure and lose more market share to Firm 1[8]. For Firm 2, (D, C) is the dominant scenario until the capacity level at Firm 1 becomes a competitive disadvantage. In other words, Firm 2 also benefits from a decentralized competitor initially. However, after a certain point, Firm 2 loses its lead-time advantage and starts to hurt from Firm 1's decentralized structure, as Firm 1 gains a larger market share given its aggressively low prices.

Observation 10 *When the intensity of lead-time competition is high and the intensity of price competition is low, the firm with higher capacity benefits from a centralized organizational structure and a decentralized competitor, although a centralized organizational structure is dominant for its competitor.*

In Figure 11, the intensity of price competition is high ($\beta/b = 3/4$), while the significance of "net own" price effects is low. Under this setting, higher prices can be quoted, and thus, both firms will be more aware of competitor prices and make their decisions accordingly. The firm with higher capacity will be able to use its competitive advantage through not only lower lead-times but also lower prices. We still observe that a decentralized structure for Firm 1 under high capacity results in loss of profits for its own as well as its competitor. Moreover, Firm 1 still benefits from a decentralized competitor, however, it now prefers to employ a decentralized structure up to a certain capacity. Lower prices under a decentralized structure can compete with Firm 2 prices effectively without hurting profits, given that the margins are already high. Beyond this point, aggressive prices driven by the marketing department generates too much demand given the flexibility provided by high capacity, which makes a centralized structure dominant. Firm 2 also benefits from a decentralized competitor until increasing capacity at Firm 1 becomes a disadvantage with a large number of customers switching to Firm 1, given its aggressively low prices and lead-times. Even though a decentralized structure provides Firm 2 lower prices to compete

[8]Note that although Firm 2 quotes lower prices in a decentralized organizational structure, Firm 1 is able to match those given its high capacity.

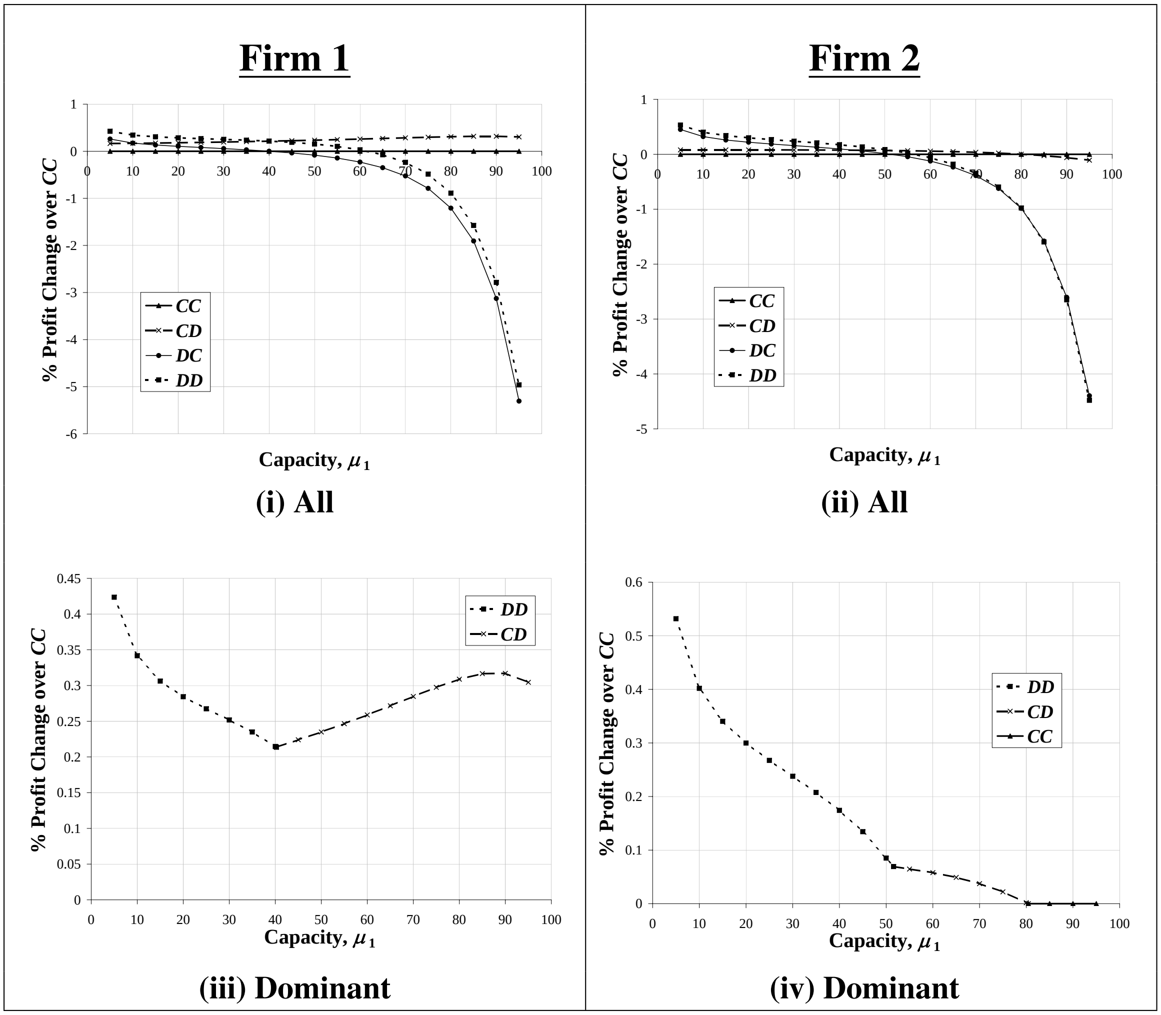


Figure 11: Comparison of Scenarios with respect to Firm 1 Capacity when the intensity of price competition is high ($\beta = 3$)

against Firm 1, in order to keep its market share as high as possible given its limited capacity, a centralized structure becomes more profitable when it cannot lower its prices further in response to Firm 1 ($\mu_1 \approx 80$), and instead chooses to compete with lower lead-times.

Observation 11 *When price competition is highly intense but less effective than lead-time competition, each firm may benefit from a decentralized organizational structure until increasing capacity at one firm becomes a disadvantage.*

Concisely, although a firm may benefit from a decentralized structure under limited capacity facing a limited capacity competitor, a centralized structure is dominant under high capacity or while competing against a high capacity firm. Docters *et al.* ([37]) discuss that employing centralized or decentralized pricing depends on the market, i.e., competitors, customers and economics, and point out the case of Home Depot. When Home Depot was at the stage of expansion following its foundation, it did not face strong competitors and employed decentralized pricing at the local store level. However, after starting to encounter strong and comparable competitors such as Lowe's, it switched to a centralized pricing structure tightly controlling prices and costs at the corporate level, which is consistent with our findings.

3.6 Special Cases

In this section, we discuss some special cases for analytical insights.

3.6.1 Price Competition for Uncapacitated Firms

In this section, we assume that both firms have constant lead-times, $L_i, i = 1, 2$, and no capacity restrictions, and thus, no reliability constraints. This corresponds to a pure marketing problem with the objective of profit maximization in the centralized organizational structure and revenue maximization in the decentralized organizational structure. The best response of firm i to firm j's price decision in the second stage is given by

$$p^*_{i(D,S_j)} = \frac{a_i - c_i L_i + \gamma_{ij} L_j + \beta_{ij} p_{j(D,S_j)}}{2b_i} \quad \text{and} \quad p^*_{i(C,S_j)} = p^*_{i(D,S_j)} + \frac{m_i}{2}$$

We solve for the unique equilibrium and observe the following:

- $p^*_{i\cdot}$ decreases in L_j if $\frac{\beta_{ij}}{b_j} > 2\frac{\gamma_{ij}}{c_j}$: If the percentage of customers that switch by price differentiation is twice the percentage of customers that switch by lead-time differentiation, price should be decreased as the lead-time of the competitor increases. Otherwise, price should be increased.

- $p^*_{i\cdot} - p^*_{j\cdot}$ increases in $L_j - L_i$: The intensity of price differentiation increases in the intensity of lead-time differentiation.

In Table 4, we compare all four scenarios for the optimal quoted prices and generated demand, where $A_1 = \frac{\beta_{12} b_2}{2b_1 b_2 - \beta_{12}\beta_{21}}$ and $A_2 = \frac{2b_1 b_2 - \beta_{12}\beta_{21}}{\beta_{21} b_1}$. We observe the following:

Table 4: Unconstrained Price Competition

$\mathbf{m_1/m_2}$	**Price**	**Demand**
$(0, \frac{\beta_{12}}{2b_1})$	$p_{1(C,C)} > p_{1(D,C)} > p_{1(C,D)} > p_{1(D,D)}$ $p_{2(C,C)} > p_{2(D,C)} > p_{2(C,D)} > p_{2(D,D)}$	$\lambda_{1(C,D)} < \lambda_{1(D,D)} < \lambda_{1(C,C)} < \lambda_{1(D,C)}$ $\lambda_{2(D,C)} < \lambda_{2(C,C)} < \lambda_{2(D,D)} < \lambda_{2(C,D)}$
$[\frac{\beta_{12}}{2b_1}, A_1)$	$p_{1(C,C)} > p_{1(C,D)} \geq p_{1(D,C)} > p_{1(D,D)}$ $p_{2(C,C)} > p_{2(D,C)} > p_{2(C,D)} > p_{2(D,D)}$	$\lambda_{1(C,D)} < \lambda_{1(D,D)} < \lambda_{1(C,C)} < \lambda_{1(D,C)}$ $\lambda_{2(D,C)} < \lambda_{2(C,C)} < \lambda_{2(D,D)} < \lambda_{2(C,D)}$
$[A_1, A_2)$	$p_{1(C,C)} > p_{1(C,D)} > p_{1(D,C)} > p_{1(D,D)}$ $p_{2(C,C)} > p_{2(D,C)} > p_{2(C,D)} > p_{2(D,D)}$	$\lambda_{1(C,D)} < \lambda_{1(C,C)} \leq \lambda_{1(D,D)} < \lambda_{1(D,C)}$ $\lambda_{2(D,C)} < \lambda_{2(C,C)} < \lambda_{2(D,D)} < \lambda_{2(C,D)}$
$[A_2, \frac{2b_2}{\beta_{21}})$	$p_{1(C,C)} > p_{1(C,D)} > p_{1(D,C)} > p_{1(D,D)}$ $p_{2(C,C)} > p_{2(D,C)} > p_{2(C,D)} > p_{2(D,D)}$	$\lambda_{1(C,D)} < \lambda_{1(C,C)} < \lambda_{1(D,D)} < \lambda_{1(D,C)}$ $\lambda_{2(D,C)} < \lambda_{2(D,D)} \leq \lambda_{2(C,C)} < \lambda_{2(C,D)}$
$[\frac{2b_2}{\beta_{21}}, -)$	$p_{1(C,C)} > p_{1(C,D)} > p_{1(D,C)} > p_{1(D,D)}$ $p_{2(C,C)} > p_{2(C,D)} \geq p_{2(D,C)} > p_{2(D,D)}$	$\lambda_{1(C,D)} < \lambda_{1(C,C)} < \lambda_{1(D,D)} < \lambda_{1(D,C)}$ $\lambda_{2(D,C)} < \lambda_{2(D,D)} < \lambda_{2(C,C)} < \lambda_{2(C,D)}$

- Prices and profits are highest when both firms are centralized and lowest when both are decentralized.

- The lowest demand for firm 1 (2) and highest demand for firm 2 (1) are generated in a hybrid scenario when firm 1 (2) is centralized and firm 2 (1) is decentralized. Moreover, being the centralized firm in a hybrid scenario does not always result in higher prices or profits than being the decentralized firm.

- In the case of identical firms, where all parameters are equal for both firms including $L_1 = L_2 = L$, we have $m_1 = m_2$ and $m_1/m_2 = 1 \in (A_1, A_2)$. We observe that being decentralized generates higher demand for both firms than being centralized. Although the decentralized firm in a hybrid scenario quotes lower prices than the centralized firm, it may generate higher profits if

  $$\frac{bm}{a - (b - \beta)m - (c - \gamma)L} < \frac{\beta}{b}$$

  Note that as β increases, the term on the left-hand side decreases, while the term on the right-hand side increases making it more likely for the inequality to hold.

This result is consistent with our findings based on Table 2 that as the intensity of price competition, (β/b), increases, the decentralized firm in a hybrid scenario may generate higher profits than the centralized firm.

We finally note that if the firms can also choose their lead-times optimally, then $L_{1.}^{*} = L_{2.}^{*} = 0$.

3.6.2 Lead-time Competition

When prices are constant, the problem turns into a pure production problem. As long as $p_i \geq m_i,\ i = 1, 2$, which we can assume to avoid triviality, the problem for the best response of firm $i = 1, 2$ under the centralized and decentralized organizational structures is given by Equation (20) for $i = 1, 2$. Therefore, the equilibrium solution under all structures is equal and given by the simultaneous solution of Equation (26) for $i, j = 1, 2,\ j \neq i$.

$$c_i L_i^2 - (a_i + \beta_{ij} p_j + \gamma_{ij} L_j - b_i p_i - \mu_i) L_i - k_i = 0 \tag{26}$$

For identical firms with the same parameters and prices, the optimal lead-times are given by:

$$L_1^* = L_2^* = \frac{a - (b - \beta)p - \mu + \sqrt{(a - (b - \beta)p - \mu)^2 + 4k(c - \gamma)}}{2(c - \gamma)}$$

We observe that the optimal lead-time decreases in the quoted price, increases in the cross price sensitivity and cross lead-time sensitivity.

3.7 Conclusions

In this chapter, we study two firms that compete on the basis of price and lead-time decisions in a common market. We analyze the impact of the decentralization of price and lead-time decisions, as quoted by the marketing and production departments, respectively, when one or both firms compete with a decentralized organizational structure. We show the existence of a unique subgame perfect Nash Equilibrium under all outcomes from the first stage of the game, where organizational structures are determined. We observe that a firm's preference for a centralized or decentralized structure, given its competitor's structure, may change depending on market and firm characteristics. Our key findings are as follows:

- When price competition is more intense than lead-time competition in the market, a centralized organizational structure is dominant for both firms.
- The firm with an increased advantage over price competition can benefit from a decentralized structure in which case the competitor prefers a centralized structure.
- A centralized structure is dominant under high capacity. Moreover, higher capacity does not always result in higher profits under competition even if it comes for free. For non-identical firms, when price competition is highly intense but less effective than lead-time competition, each firm may benefit from a decentralized structure until increasing capacity at one firm becomes a disadvantage.
- For identical firms, when the intensity of price competition is high but less effective than lead-time competition, firms may benefit from a decentralized structure even under high production costs.

CHAPTER IV

AN EMPIRICAL STUDY FOR ESTIMATING PRICE ELASTICITIES IN THE TRAVEL INDUSTRY

4.1 Introduction

Revenue management (RM) refers to the strategy and tactics of managing capacity by controlling price and availability to maximize revenue [100]. RM has originated from passenger airlines, and is frequently used in the travel and hospitality industry, i.e., airlines, hotels, rail operators, car rental agencies, etc., where inventory is perishable. In other words, once a plane departs, unsold capacity is wasted.

In passenger travel industry, a product is defined by an itinerary, i.e. an origin-destination pair and a departure date, on the resource (e.g., aircraft, train). Product differentiation becomes important when different types of customers have different willingness to pay. In general, business customers are less sensitive to price and book closer to the day of departure, while leisure customers are more sensitive to price but can accept reduced flexibility in a form of advanced booking or Saturday night stay for lower prices. Market segmentation, which is used to define various types of products (or virtual products as referred in [100]), is usually based on (i) compartments (e.g., first class, business, economy), (ii) restrictions on the ticket (e.g. advance purchase, Saturday night stay, non-refundable).

In RM systems, inventory is controlled by buckets or fare classes. In traditional RM, fare classes are defined by a set of restrictions on who can purchase the product and when and associated prices. Protection/authorization levels need to be set for each fare class such that high fare seats are protected until a few days before departure from the "low fare" leisure travelers. A nested fare class approach, where each fare class has access to all of the inventory available to lower-fare classes, is common for capacity allocation. The business problem in traditional RM is to choose which fare classes to open and close at a given day-to-departure to maximize revenue.

Over the past few years, the passenger travel industry has been transformed by the increasing availability of low-cost carriers, the visibility offered by the internet, and customers becoming more conscious of low prices [60, 22]. Thus, carriers tend to decrease the range of restrictions and offer a limited number of differentiated products at a range of multiple prices, which are mapped to different fare classes. When fare classes become different price points for the same product, customers tend to book in the class with the minimum available fare. A traditional RM system will observe this phenomenon as decreased demand for higher fare classes, and forecasts will overestimate low-fare demand at the expense of high-fare demand and set lower protection levels for higher fare classes. Customers then book at the lower price point leading to a *spiral-down* of revenues as more tickets are made available at the lower fare class [32].

In this new context, where there is no clear fare order and fare class demand depends mainly on which other classes are open, new RM systems also need to assist in choosing which products to offer and the associated price points for those products [60]. In order to better serve this purpose, accurate estimation of the price sensitivity of customers plays an important role. JDA Software Group, Inc., a leading solutions and software provider in pricing and revenue optimization, reports that "Price-Sensitive Revenue Management is all about understanding customer price sensitivity - not just about managing booking classes" [60]. In this chapter, we explore how to obtain better price sensitivity estimates through an empirical study based on the data of one of the international high speed rail operator clients of JDA Software.

When estimating market response models and calculating price elasticities based on historical data, a phenomenon that deteriorates the quality of the model estimates is endogeneity. A price endogeneity problem can arise when the price determination process involves significant interplay of supply and demand. Such interaction may result in simultaneous equation bias, which corresponds to bias and inconsistency in the least square estimates of demand parameters. Price endogeneity is particularly relevant in analyzing demand for differentiated products [36]. Bijmolt *et al.* ([16]) present a meta-analysis of price elasticity with new empirical generalizations on its determinants based on 81 studies, and find that accommodating price endogeneity has strong impact on price elasticities.

The endogeneity problem has been widely studied in retail contexts, and although it is quite prevalent in RM contexts, published work in this area is lacking. Talluri and van Ryzin ([121]) discuss endogeneity and heterogeneity as two nonstandard estimation problems that are of particular importance for RM applications. When carriers observe or anticipate high demand, they often react by raising their prices, which results in high price-high demand and low price-low demand pairs in the data. This is especially true as it gets closer to the day of departure or during high season periods such as Christmas, summer, etc. Several studies in the retail industry have shown that the estimate of the price response parameter is biased downward when the endogeneity of prices are ignored ([11, 13, 31, 130]). In this study, we empirically demonstrate the presence of the endogeneity problem in a passenger travel context using data from an international high speed rail operator from Europe. We consider the impact of both price and time-related factors on the number of tickets sold for a specific origin-destination pair. We group trains that show a similar demand pattern during the day through a mixture of Gaussians approach, creating departure time slots that define 'Morning', 'Afternoon' and 'Evening'. We estimate separate regression models for each market classification group, which we define by point of sale country (outbound vs. inbound trip), compartment (first/economy), advance vs. late purchase, Saturday night stay and departure time slots. The major difficulty in this problem arises as a result of the significant increase in the number of tickets sold as it gets closer to the day of departure, while the prices also increase. Thus, the "days left to departure" component introduces a secondary time dimension into the problem besides the departure date, which differentiates the nature of the problem from typical retail contexts. In order to control for endogeneity, we employ an instrumental variable approach via two stage least squares estimation (2SLS). As instruments, we choose to include the average prices lagged by “reading days", which are different days left points at which the observed demand is checked against inventory and lower fare buckets are closed as necessary, for each departure date and classification group. We contrast the results from the 2SLS estimation with those from the ordinary least squares (OLS) estimation. We show that if one does not account for endogeneity, price elasticities may induce an upward-sloping demand curve suggesting that high price produces high demand, or may be biased downward to the extent that elastic demand curves are incorrectly classified as inelastic. The estimated price elasticities are also found to be intuitive as advance purchasers with Saturday night stay being the most elastic market segment.

The organization of this chapter is as follows. We begin by presenting a theoretical background on the endogeneity problem in market response models along with a summary of the relevant literature both in retail and travel contexts. In Section 4.3, we provide a preliminary analysis for insights on the data characteristics identifying important factors and defining market segments. We also show the results from a “*naïve*” OLS regression model. In Section 4.4, we redefine our regression model and introduce instrumental variables. We provide a comparison of the estimation results from OLS and 2SLS models, and discuss the insights for both the economy and first classes. We conclude the chapter in Section 4.5.

4.2 Literature Review

4.2.1 Endogeneity in Market Response Models

Endogeneity is a common problem encountered while estimating coefficients of market response models based on historical data, and results from the interaction between supply and demand. The endogeneity problem is more prevalent in naturally occurring data than in traditional market research data such as those collected by questionnaires or surveys, and is less of a problem for experimental data [111]. It has been studied widely in retail contexts, especially on brand choice models, where it arises when there are variables for which data are not available, i.e., demand shocks that are unobservable to the researcher such as shelf space allocation, unobserved advertising or coupon availability, changes of prices of competing goods, changes in the economic outlook or weather, etc. or demand shocks that are difficult to quantify for the researcher such as aspects of style, prestige, reputation, past experience, which could influence a brand's sales in the given period [129]. These other marketing activities are part of the error term in the estimation and the endogeneity problem arises as a result of the correlation between the price variable and the error term. Not accounting for this correlation will give incorrect estimates for the effects of the included marketing variables or demand curves sloping upward in price [30, 12].

In empirical studies, researchers have used two approaches to control for price endogeneity. The first approach is the full information approach, which involves the explicit specification of supply equations reflecting strategic firm behavior and the simultaneous estimation of both demand and supply equations. Several researchers employ a full-information approach, and find that the estimates of the price response parameter are biased downward when the endogeneity of prices are ignored. Dhar *et al.* ([36]) test for price and expenditure endogeneity on market-level sales data of soft drinks using a disaggregate nonlinear almost ideal demand system (AIDS) model, and find that both price and expenditure endogeneity significantly impacts the consistency of demand parameter estimates. Draganska and Jain ([39]) develop a likelihood-based method and specify an individual-level discrete-choice model of demand and derive the supply side assuming Bertrand-Nash competition in prices among manufacturers. Prices and choice probabilities are simulated by solving for the market equilibrium. Yang *et al.* ([139]) develop a hierarchical Bayesian method for estimating simultaneous demand and supply models with applications to both the analysis of household panel data and aggregated demand data. The method is developed within the context of a heterogeneous discrete choice model coupled with pricing equations derived from competitive structures, such as Bertrand equilibrium, or linear equations used in instrumental variable estimation. Villas-Boas and Zhao ([130]) model the demand side through a latent utility framework that allows for a no-purchase option and the supply side through the profit-maximizing decisions of multiple manufacturers and a multi-product retailer. The authors find that not accounting for demand endogeneity can create bias in the estimation, where the retailer prices are below the profit-maximizing prices for two of the three brands, and the marginal wholesale prices are below the Nash equilibrium uniform wholesale prices for two brands. Besanko *et al.* ([13]) model prices as the equilibrium outcomes of a Nash competition among manufacturers and retailers with a logit demand model, and find that the price endogeneity effect is statistically significant and the estimates of the price response parameter are biased downward when the endogeneity of prices are ignored.

Capturing the strategic properties of pricing in a simple model may be difficult, and imposing the wrong supply-side model will contaminate the estimates for the demand parameters [31, 129]. In [128], it is shown that if the assumptions made in the full information model are not true, then the full information approach may yield inconsistent estimates for the parameters, while a limited information approach may still yield consistent estimates if the "limited" information is true. The limited information approach is more flexible and involves the instrumental variables (IV) technique, where a set of instruments that are correlated with the endogenous variable but uncorrelated with residual errors need to be determined [92]. Although nonlinearity of the demand model makes the application of the IV technique difficult in a discrete-choice utility framework, the IV technique is a straightforward application for consistent estimation of demand parameters in linear models such as the constant elasticity model. For a comparison of full information estimation with limited information estimation in non-linear models, the reader is referred to [128]. All exogenous variables in the utility/demand equation plus lagged prices [30, 129, 139, 68], wholesale prices (or costs) [129, 31, 115] and own/cross product characteristics [11] are among the commonly used instrumental variables. Note that in cases where forward buying and stockpiling are prevalent, lagged prices could be correlated with the utility equation error terms, which would make lagged prices inappropriate instruments [129].

Villas-Boas and Winer [129] test price endogeneity using simulated maximum likelihood on scanner panel data from two product categories, while Kuksov and Villas-Boas ([68]) present a quasi-likelihood method to consistently estimate parameters and test for endogeneity under unobserved consumer heterogeneity, common shocks, and endogenous firm behavior through differences in GMM coefficient estimates of a model with and without instrumenting for the explanatory variables. Blundell and Powell ([17]) develop semiparametric methods for estimating binary choice models with continuous endogenous regressors. The approach to detect the presence of endogeneity in [129, 17] is generally referred to as a control function approach, where the endogenous variable is regressed against exogenous instruments, and the residual from this regression is entered as an additional explanatory variable in utility. Another widely used approach for dealing with endogeneity in discrete choice models is the BLP approach [12, 11], which uses an inversion procedure to transform the nonlinear choice function into a linear one in price, allowing standard IV procedures to be used. The BLP method is particularly useful since the distribution of errors around their conditional means need not be known or estimated. Using this procedure on aggregate data in the automobile market, Berry *et al.* ([11]) find that ignoring price endogeneity lead to price response coefficients that are only about half as large as they are under instrumental variables techniques. Chintagunta ([30]) proposes a probit model, which avoids the independence of irrelevant alternatives (IIA) property that affects the logit model at the individual consumer level, to specify the aggregate demand functions of firms competing in oligopoly markets. Chintagunta *et al.* ([31]) use a random-coefficients logit model to account for the presence of unobservable product attributes and employ an IV approach. They use household panel margarine data for empirical analysis. Song and Chintagunta ([115]) study the cross-category effects of marketing activities using a second-order

Taylor series approximation to an arbitrary utility function to represent bundle utility on aggregate store level data. Petrin and Train ([99]) develop a class of overidentification tests of specification, which include both conditional moment and control function type tests, for the problem of omitted attributes in differentiated product models. The first stage in the estimation method is a regression and the second stage is maximization of a likelihood function. The approach is tested on three empirical applications; television reception options for household-level cross-sectional data in [99] and automobile market for aggregate data and margarine for household-level panel data in a later work [98].

So far, we have mainly discussed the endogeneity problem in discrete choice models. However, double-logarithmic, or equivalently, constant elasticity models are still very popular in RM practice, although there is a movement towards choice modeling [120, 126]. When a linear demand model is compared with a discrete choice model, one favors the latter as it requires estimation of fewer parameters (including own and cross effects), as compared to the former. Moreover, it seldom results in parameter estimates with incorrect signs for own and cross effects, as is the case with linear demand systems and their variants. Chintagunta ([30]) estimates the demand function parameters of a log-log model in comparison with a probit model for brand choice and finds that the estimated elasticities could be signed in such that they are not useful for firm-level pricing decisions. Song and Chintagunta ([115]) compare the estimated elasticities from their logit model to those obtained from the log-log regression model and also find that the proposed model produces more reasonable estimates. The biggest drawback of a discrete choice model under the RM context is that it requires the total market size as well as competitor information, which are not readily available. It is still possible to construct a discrete choice model using different itineraries/product types as alternatives, but it is quite challenging. As most of the current RM systems still use a log-log model, we also use a log-log model for our analysis, and leave discrete choice modeling for future research.

We next give a brief theoretical summary for endogeneity. Consider the following regression model:

$$y = \alpha + \beta x + \epsilon \tag{27}$$

where y is the dependent variable (n x 1), x is the set of independent variables (n x K) and ϵ is the error term. One of the assumptions of ordinary least squares (OLS) is that $COV(x, \epsilon) = 0$, where COV represents the covariance function. In case of endogeneity, $COV(x, \epsilon) \neq 0$ and standard OLS estimates are inconsistent, i.e., as the sample size approaches infinity, the estimates of the parameters on average will not equal the population estimates. One of the most common approaches to control for endogeneity is the two-stage least squares regression (2SLS) method, which is a type of IV procedure. In order to implement 2SLS and obtain consistent parameter estimates, the selected instruments, z (n x L), must satisfy two conditions:

1. $COV(z, \epsilon) = 0$.

2. $COV(z, x) > 0$.

The only condition for identification is that there should be a sufficient number of instruments for the independent endogenous variables that are fully correlated with these variables. Typically, all exogenous variables in the original OLS equation and external variables at least as many as the number of independent endogenous variables are used as instruments in the first stage OLS ($L \geq K$). Then, the 2SLS procedure gives the parameter estimates as follows:

1. Run the first stage OLS regression for x on z, and get predictions for x; $\hat{x}$.

2. Run the second stage OLS regression for y on $\hat{x}$.

There are mainly two methods to test for the presence of endogeneity.

- Regression of an endogenous variable on a set of exogenous variables generates residual errors that uncover information related to the bias in demand-side errors.

The resulting residuals are used as an independent variable in the demand specification and tested for the significance of the corresponding parameter, which would indicate that the unexplained variation of the endogenous variable also affects the variations in demand, implying the endogeneity of the variable. This method is employed in [129].

- The other approach tests for the consistency of parameter estimates, and is known as the Hausman (or Durbin-Wu-Hausman) test [54]. First, the potential endogenous variables in the demand system are identified. The test is based on the difference between parameter estimates with and without controlling for potential endogeneity. The null hypothesis is that parameters estimated without controlling for endogeneity are consistent. Rejecting the null hypothesis implies endogeneity of the explanatory variables. SUR (seemingly unrelated regression) estimator provides consistent estimates of the demand parameters under the null hypothesis. 2SLS (two-stage least squares) estimator is consistent under both cases. 3SLS (three-stage least squares) is consistent when prices are endogenous. In [68], endogeneity is tested via the differences in generalized method of moments (GMM) coefficient estimates of a model with and without instrumenting for the explanatory variables. The Hausman test statistic is

$$H = (\beta_{IV} - \beta_{OLS})^T \left[SE^2(\beta_{IV}) - SE^2(\beta_{OLS})\right]^{-1} (\beta_{IV} - \beta_{OLS}) \tag{28}$$

  and is distributed as a chi-square variable with degrees of freedom equal to the number of variables being tested for endogeneity.

If valid instruments are selected, the correlation between the error term and the independent variable becomes corrected using the fitted values of the independent variable through the instruments. Note that the standard errors from the two-step procedure will be incorrect, and therefore, it is recommended to use a direct 2SLS/IV approach from statistical packages such as SAS, STATA, etc. As the number of instruments gets larger, more efficiency is obtained. However, the small sample bias of the estimator may get worse and since degrees of freedom are lost, the power of statistical tests will weaken. Sargan ([109]) suggests an over-identification test that checks whether the extra instruments, which over-identify the model, are valid for the specification.

1. Regress the second stage residuals against all the instruments and get the R^2.

2. Form the test statistic: NR^2, where N is the sample size.

3. The test statistic has a chi-square distribution with degrees of freedom equal to the number of instruments less the number of right hand side (RHS) variables in the original equation ($L - K$).

4. If the statistic is significant, then an over-identification problem exists.

4.2.2 Price Elasticity Estimation in Passenger Travel Industry

To the best of our knowledge, we are the first empirical work to consider price endogeneity in the passenger travel industry incorporating concepts specific to RM, such as price changes at different days left to departure and availability controls, along with the time component, such as departure date and time, and market segmentation. There have been some recent studies that try to find out the determinants of air fares such as [117, 127, 82]. In [117], the research question is whether price discrimination increases with competition in the market. A log-linear price regression model is used, where some of the factors considered are the market share of the airlines, distance between origin and destination, last day prior to the departure where the fare was offered, advance purchase, Saturday night stay and a first class dummy. The data is cross-sectional pertaining to Thursdays only. In [82], a dynamic price discrimination model with price commitment is considered. Price regression is performed on data collected from airline/agent websites for three days of the week for five weeks. Some of the independent factors that are included in the model are days left to departure, weekly indicators, time of day indicators, airline indicators and origin specific factors. In [127], the effect of internet on air fares is explored and it is found that the internet transparency increases the spread between restricted and unrestricted fares. A market-level hierarchical random effects model is used for price regression. The factors that are considered are origin-destination specific factors (such as income and population size), distance, oil prices and time-level random effects, where time refers to the time spent in internet search activities.

There have also been studies that estimate price elasticities for passenger air travel with endogeneity considerations. In [25, 51, 62], intercity air travel is considered on cross-sectional aggregate demand data. Both papers include flight frequency, aircraft size, travel time and income as independent variables. In [51], price is chosen as the weighted average airfare per class, where the classes are economy, unrestricted economy and business, and is treated as an endogenous variable. The instrument for 2SLS is selected as a Herfindahl index calculated as the sum of the squares of flight frequency shares of each airline in the market. In [62], the price variable is chosen as the cheapest unrestricted economy fare, and indicators for the existence of moderately and highly discounted fares are included. Flight frequency, aircraft size and price are treated as exogenous, and total capacity volume on the route, country specific dummies and dummy for deregulated markets are used as instruments for 2SLS. In [25], a similar setting is considered, however, fare elasticities are estimated per route at a specific airline level. Time component is also considered. Daily demand for two months in three years is aggregated at the level of two main fare classes; business and economy. Year and weekend indicators are also included as independent variables. Frequency of flights is the only endogenous variable in the model, however, the authors do not find a significant difference between the OLS and 2SLS estimates with fuel costs as instruments.

In [4], the effect of quality of service, which is defined as the frequency delay difference between the desired and nearest offered departure time and unavailability of one's preferred nearest departure date, is explored. Monthly data for business and leisure classes between different origin and destination pairs are considered in simultaneous equations. Price is defined as the "full trip price", which is the airfare plus the value of time. Lagged dependent variables are included in the model. 1-month lagged price variables are used as instruments for 2SLS. In [52], price transparency from online agents is studied using cross-sectional data for one year between origin destination pairs. Tickets sold are aggregated by agency type (Expedia, Travelocity, Orbitz, Hotwire, airline website or offline), time of purchase (days left to departure) and season (peak/off-peak). Travel time, agency dummies and income are also included. Instruments for price are selected as mileage, online agency dummy and Herfindahl index, which is the sum of squares of the market shares of the different airlines that serve a city-pair, but endogeneity is not found to be significant. In [94], the full information approach is employed for endogeneity. Simultaneous duopoly and monopoly equations are estimated using aggregated quarterly data of two competitors, American Airlines and United Airlines. The price is defined as the average weighted price charged per passenger on a given route by an airline. Cost per passenger mile is included for supply side modeling. A similar setting is also considered in [10], where the available data are aggregated to the level of the airline/route/fare on a quarterly basis. In either paper, capacity, days left to departure or ticket restrictions are not considered. Finally, [10] introduces an explicit unobserved product characteristic, which is correlated with prices, to help control for these unobserved restrictions and uses the BLP approach on a logit model, where product price, product market shares and spoke densities are treated as endogenous. Instruments for spoke densities are chosen as population and network characteristics at the endpoint cities, and additional instruments for price and markups include the characteristics of other products in the market.

4.3 *Preliminary Data Analysis*

The passenger rail industry is very close to the passenger air industry in terms of the principles of the RM systems with some differences on the product definition; a smaller range of restrictions, and fewer price points. The structural differences are that:

1. Passengers can usually buy tickets on the train,
2. There are various stations between the end points of a train's origin and destination, so passengers can get on/off at any station
3. There is usually excess/inflexible capacity,
4. There is a large number of trains that run per day for the same origin-destination pair.

As in [25], we consider price elasticity estimation at a specific company level in contrast to all the studies based on aggregate origin-destination demand. The company of interest is one of the international high speed rail operator clients of JDA Software Group, Inc. High-speed/long-haul rail operators are closer to airlines, and their major competitors are low cost air carriers. They use advanced booking and 100% check-in. Given the long-haul structure of the business, only the major origin-destination pairs are of interest for us. We also note that since the trains are almost never full, capacity is rarely an issue. Therefore, we do not consider unconstrained demand within the scope of this study.

The company's RM system lies between a traditional RM system and a "lowest available fare" system:

- There are two compartments; first class and economy.
- There are several product types per compartment. Each product type is mapped to a fare class, where fare classes represent different fare levels.
- Only one fare class is *effectively* on sale at any one time (lowest available fare for the product type).

- Fare classes are opened and closed with control over availability to change prices for a range of product types.

We use the SAS software for all statistical analyses in this chapter. We analyze ticketing data for all trains operating in the time period of April 2004 - March 2005 from station "ABC" to station"DEF", which is a major international market[1]. Note that we consider directional routes, i.e., ABC to DEF is a different market than DEF to ABC. Therefore, for round-trip tickets, we calculate the price paid for each direction of the trip as half of the price for the round-trip ticket. Note that for this company, one-way tickets are mostly half the price of round-trip tickets, so passengers cannot save much by purchasing round-trip tickets as it is usually the case for airlines. We also exclude group and special pass ticket sales out of the analysis as the pricing structure for those fare types are different. Moreover, we exclude trains that constitute less than 1% of the total ticket sales over the period of study, as those were found not to be trains of regular operation. Table 5 lists the major factors/components that we consider in this chapter. The rest of the factors are introduced later in the chapter. We also use the prefix of '*ln*' to denote the log-transformation of each variable ($ln\_Pax = log(Pax)$).

We expect to have differences in price elasticity at a minimum with respect to origin, destination, compartment and advance purchase. Therefore, we consider four market segments ($MktSegType$):

- 'FrstAdvn': First Class compartment, advance ticket purchase ($\geq$ 21 days left to departure)
- 'FrstLate': First Class compartment, late ticket purchase ($<$ 21 days left to departure)
- 'EconAdvn': Economy Class compartment, advance ticket purchase ($\geq$ 21 days left to departure)

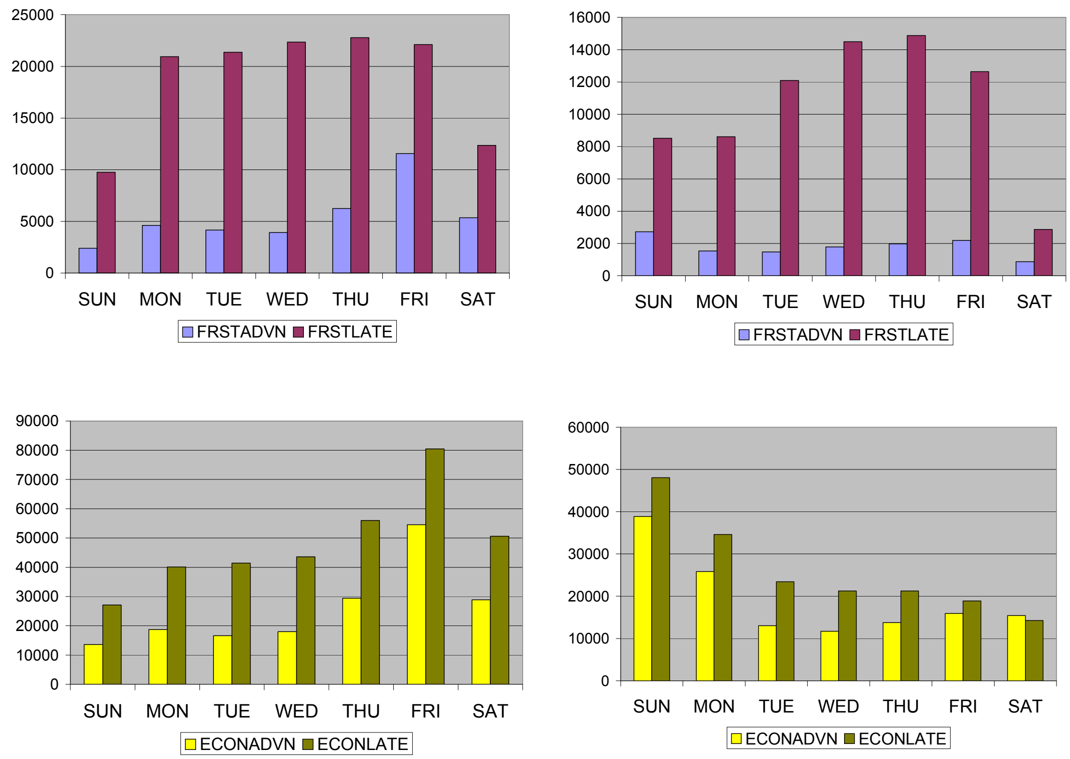
[1]Due to confidentiality concerns, we mask company specific information.

Table 5: Factors/components for the data analysis

Factor Name	Factor Description
Pax	Number of tickets sold
$AvgFare$	Average price paid for the (one-way) trip
$MedFare$	Median price paid for the (one-way) trip
$Cmpt$	Compartment, 'Frst' for first class and 'Econ' for economy
$MktSegType$	Market (customer) segment type
PoS	Point of sale country, 'A' for 'ABC and 'D' for 'DEF'
Dow	Departure day of week
$Month$	Departure month
$DeptTime$	Departure time
$DeptDate$	Departure date
$DaysLeft$	Days left to departure
$PubHol$	Public holiday indicator
$SatStay$	Indicator for ticket purchases with a Saturday night stay
$Nconn$	Number of intermediate stops if the train is not direct

- 'EconLate': Economy Class compartment, late ticket purchase ($<$ 21 days left to departure)

The reason for having a cutoff at 21 days is that purchases at least 21 days in advance are announced to be discounted at the company website. Thus, the customer is aware of this information at the time of making a purchase. After converting all prices into a single currency unit, we saw that prices paid by 'A' customers could be different than those paid by 'D' customers for the same trip. So, we also expect to see a differences in price elasticity with respect to point of sale country. Note that in general, 'ABC' to 'DEF' would denote the outbound trip for a ticket sold in 'A', while it would denote the inbound or return trip for a ticket sold in 'D'. Next, we examine how the number of tickets sold changes with respect to the time factors in the problem. In all of the following figures, we display the aggregated demand with respect to the variables in the $x - y$ axes and the specified classification variables. Although time series forecasting is common for passenger travel data, given the shortness of the history in our study, we capture seasonality with indicator variables for day of week and month. Figure 12 displays the number of tickets sold with respect to the departure day of week for each point of sale country and market segment.



(i) $PoS =$ ‘A’ (ii) $PoS =$ ‘D’

Figure 12: Number of tickets sold vs. Departure day of week

We can make the following observations from Figure 12:

- First class late purchases are relatively low during weekends and uniformly distributed during week days, which suggests that those purchases are mostly by business travelers. For return trips, Monday’s volume is not as high as that of the other days within the week, which is expected since return trips are more likely to occur towards the end of the week for business travelers.

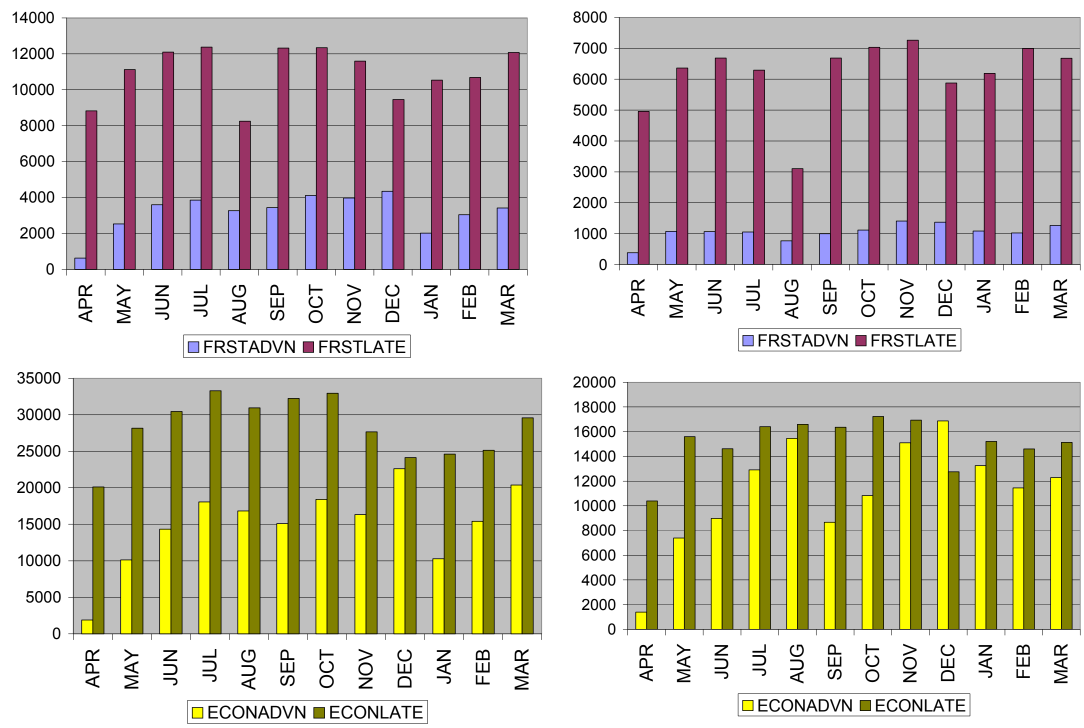
- Clearly, Friday is a peak day for outbound economy class purchases, which suggests that those are leisure travelers that are traveling for the weekend. Likewise, Sunday and Monday are peak days for return trips, which suggests that those are also leisure travelers who spent the weekend in ‘A’ and are now returning back to ‘D’.

- First class advance purchases for outbound trips have a peak on Friday suggesting that those are also leisure travelers who are willing to pay more or are willing to travel first class. A similar observation (although not as strong) can be made for return trips peaking on Sunday for first class advance purchases.

- There is not a strong difference between late vs. advance economy class purchases in terms of the day of week preference. However, late purchases are mostly higher than advance purchases. This might be due to the fact that some cost-conscious business travelers prefer economy class travel for week days, and/or that for some travelers, purchasing a ticket more than 21 days in advance is still too early for rail travel.

We next analyze the behavior of ticket sales with respect to the departure month in Figure 13. We see that month preference is not as strong as day of week preference. Also, the advance ticket purchases in April are quite low as compared to those in the other months, which might be caused by the company changing some of their advance products. Thus, we exclude the month of April from advance purchase analysis not to bias our results down, and from late purchase analysis for consistency. For the first class late purchases, we see that August has the lowest volume, as it is the most common month in Europe for use of vacation days. For economy class advance purchasers, December is an active month, most probably due to Christmas, followed by a decrease in sales in January. A similar behavior is observed in August followed by September for return trips of economy class advance purchasers, which might be due to back-to-school activity.

The third time component is the departure time of each train. For this route ('ABC' to 'DEF'), on the average, 10-12 trains operate every day. The specific times and the frequency of service depends on the day of the week. Since including each individual train leads to sparsity in the problem, we create time slots (define 'Morning', 'Afternoon' and 'Evening') to group trains that show a similar behavior. One might consider arbitrarily defining Morning to end at, say, 10am and Afternoon at 4pm. However, no sharp boundaries or breakpoints can be seen in the data to exist between Morning, Afternoon



(i) $PoS =$‘A’ (ii) $PoS =$‘D’

Figure 13: Number of tickets sold vs. Departure month

and Evening, and furthermore, the time slot characteristics differ by day of week. Accordingly, we pursue the following data-driven approach for determining appropriate temporal boundaries between the Morning, Afternoon and Evening time slots. Given the histogram of the ticket sales distribution with respect to departure time, we find a multi-modal Gaussian distribution that covers the histogram as much as possible through the expectation-maximization method. Hence, the valleys (local minima) of this aggregate distribution defines the end points of our time slots. Since the departure times depend on the day of week, and point of sale country and compartment are the major factors for determining the day of week preference, we create distinct time slots (clusters; $TimeSlot$) for each PoS, $Cmpt$ and Dow combination. We model the ticket sales distribution for outbound trips ($PoS =$‘A’) as a mixture of three Gaussian functions while that for inbound trips ($PoS =$‘D’) as a mixture of two Gaussian functions since there was not much ticket sales for the early hours for return trips. The specifics of the expectation-maximization method and the complete list of the parameters and valleys of each time slot is given in the Appendix. Examples of our derivation for each point of sale country can be seen in Figures 14 and 15. In both figures, the histogram of ticket sales with respect to departure time is given in the lower portion of the figure. A mixture of three (two in Figure 15) individual Gaussian distributions, which are displayed in the upper portion of each figure, is created as the weighted sum of those distributions, and is displayed as the light blue series in both the upper and lower portions of each figure. The valleys of these distributions give time slots of 5:00-9:50, 9:51-16:15 and 16:16-23:59 for Figure 14, and 5:00-13:35 and 13:36-23:59 for Figure 15.

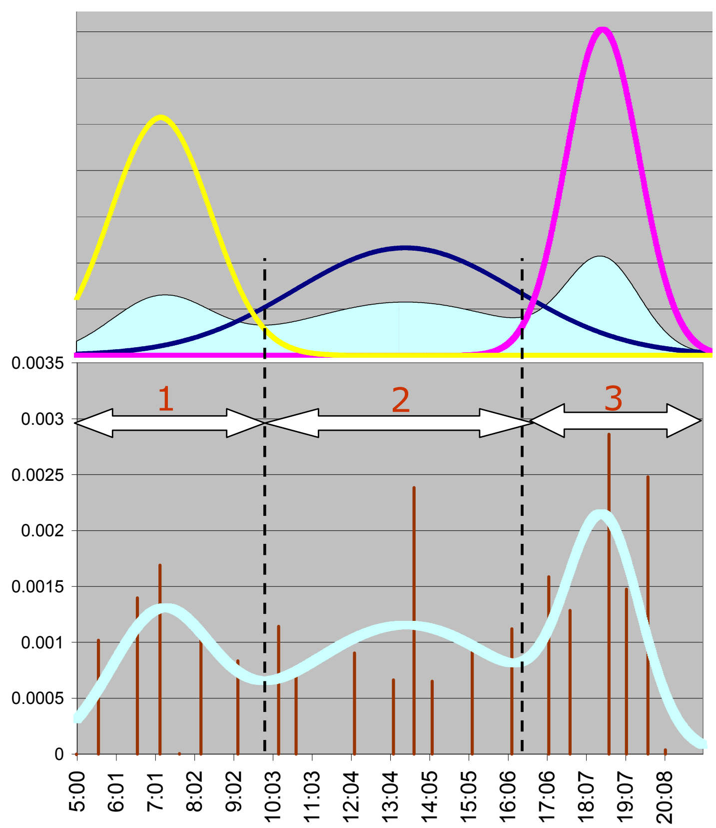


Figure 14: Multi-modal Gaussian fit for creating outbound trip departure time clusters (*PoS*=‘A’, *Cmpt*=‘Econ’, *Dow*=‘Fri’)

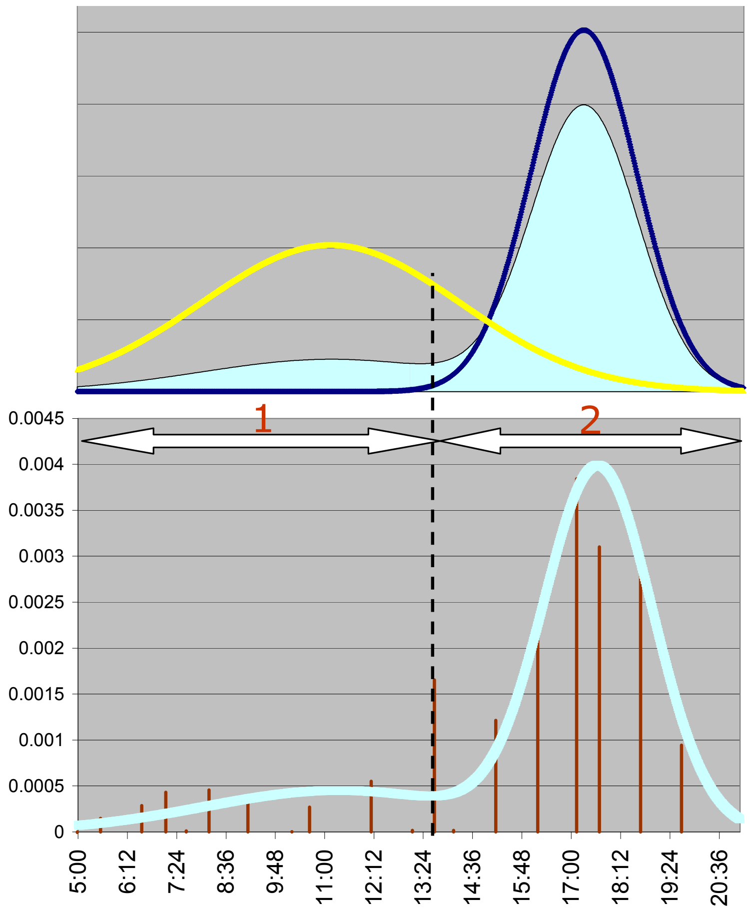
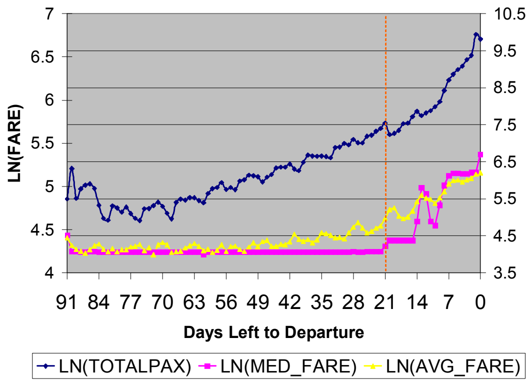


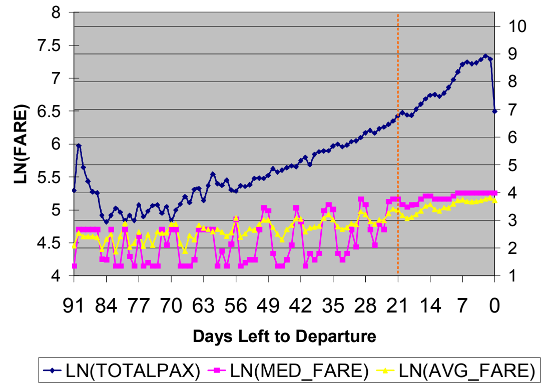
Figure 15: Multi-modal Gaussian fit for creating inbound trip departure time clusters (*PoS*=‘D’, *Cmpt*=‘Frst’, *DOW*=‘Tue’)

The final time component is the days left to departure, which makes this problem more difficult than typical time series problems because of the addition of a second time dimension related to how the tickets are sold over time. Figure 16 clearly signals the potential endogeneity phenomenon that we have in this context. The number of tickets sold increases as it gets closer to the departure date, but so does the average ticket price that was paid.

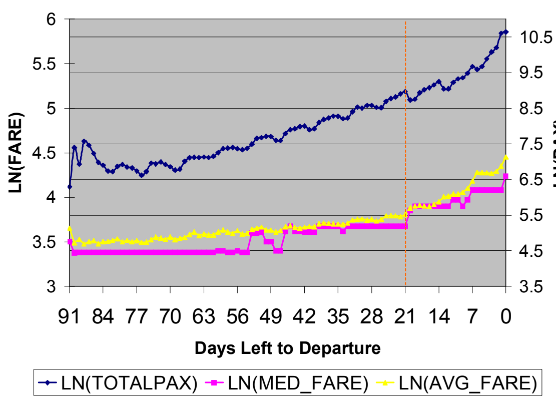
Because of data sparsity, we aggregate individual ticket sales at the level of PoS, $TimeSlot$, $MktSegType$, $DaysLeft$, $DeptDate$ and $SatStay$, and we drop each level for which no ticket sales were observed. We calculate the average price paid ($AvgFare$) and the average number of stops ($AvgConn$) at each level as weighted by the number of tickets



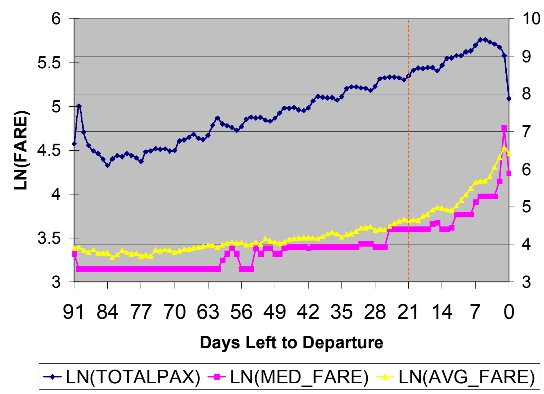
(i) $PosS$ = 'A', $CMPT$ = 'Frst'



(ii) PoS = 'D', $Cmpt$ = 'Frst'



(iii) PoS = 'A', $CMPT$ = 'Econ'



(iv) PoS = 'D', $Cmpt$ = 'Econ'

Figure 16: Number of tickets sold vs. Days Left to Departure

sold. We use 6 indicator variables corresponding to each day of the week (Mon, Tue, Wed, Thu, Fri, Sat, Sun), where one indicator is dropped for the reference day of the week, 10 indicators corresponding to each month (Jan, Feb, Mar, May, Jun, Jul, Aug, Sep, Oct, Nov, Dec), where one indicator is dropped for the reference month, and two indicators for each time slot ($TimeSlot_1$, $TimeSlot_2$, $TimeSlot_3$), where one time slot is dropped for the reference time slot. We start with the following log-log regression model, where Tue is the reference day of the week, Mar is the reference month, and $TimeSlot_3$ is the reference time slot of the day ($TimeSlot_1$ is the reference time slot of the day when PoS ='D' and it is dropped from the model):

$$\begin{aligned} ln\_Pax = \quad & ln(\alpha) + \beta(ln\_AvgFare) + b_0(DaysLeft) \\ & + b_1Sun + \ldots + b_6Sat + b_7Jan + \ldots + b_{16}Dec \\ & + b_{17}TimeSlot_1 + b_{18}TimeSlot_2 \\ & + b_{19}PubHol + b_{20}ln\_AvgConn \end{aligned} \tag{29}$$

We first analyze the Pearson correlation coefficients of all the factors in Equation (29). Table 6 displays the significant correlations related with the main variables of interest, *ln_Pax* and *ln_AvgPrice*, that are greater/less than $+/-0.20$. We can see negative correlation between days left to departure and the number of tickets sold as well as the average price paid, confirming our observations from Figure 16 that more tickets are sold and higher prices are paid as it gets closer to the departure date. The correlation is stronger for late purchases. We also observe that average prices tend to decrease if the ticket includes a Saturday night stay, particularly for late purchases. Therefore, we use $SatStay$ as a classification variable in our regression. Basic statistics on gross ticket fare can be found in the Appendix, which further illustrate the difference in the prices paid when there is a Saturday night stay.

Table 7 summarizes the OLS regression results on Equation (29). We only display the R^2 and the estimated coefficient of $ln\_AvgFare$, $\hat{\beta}$, for each classification group. Note that the regression coefficient of price in a constant elasticity model directly gives the price elasticity. We can see that if a "*naïve*" regression model is used, all price coefficients (except one) come out as positive. Moreover, although we do not expect high R^2's because of the high variability that is inherent in the problem, the R^2's from Model 0 still look quite low for all classification groups. In the next section, we redefine our model structure and incorporate instrumental variables to account for endogeneity.

Table 6: Pearson Correlation Coefficients for Model 0

Group		**Pair of Variables**		**Pearson Corr. Coefficient**
PoS	$MktSegType$			
'A'	'EconAdvn'	ln_Pax	$DaysLeft$	-0.24
			Fri	+0.22
		$ln\_AvgFare$	$DaysLeft$	-0.26
			Fri	+0.23
'A'	'EconLate'	ln_Pax	$ln\_AvgFare$	+0.32
			$DaysLeft$	-0.41
			Fri	+0.20
		$ln\_AvgFare$	$DaysLeft$	-0.40
			$SatStay$	-0.40
'A'	'FrstLate'	ln_Pax	$ln\_AvgFare$	+0.38
			$DaysLeft$	-0.44
			$SatStay$	-0.25
		$ln\_AvgFare$	$DaysLeft$	-0.31
			$SatStay$	-0.38
			Sat	-0.22
'D'	'EconAdvn'	ln_Pax	$DaysLeft$	-0.27
			Sun	+0.26
			$SatStay$	+0.24
		$ln\_AvgFare$	$DaysLeft$	-0.26
			Fri	+0.28
'D'	'EconLate'	ln_Pax	$TimeSlot_2$	+0.31
		$ln\_AvgFare$	$DaysLeft$	-0.42
			$SatStay$	-0.48
			Fri	+0.21
'D'	'FrstAdvn'	ln_Pax	$DaysLeft$	-0.21
		$ln\_AvgFare$	$SatStay$	-0.55
			Sun	-0.31
'D'	'FrstLate'	ln_Pax	$ln\_AvgFare$	+0.28
			$DaysLeft$	-0.24
			$SatStay$	-0.32
			$TimeSlot_2$	+0.29
		$ln\_AvgFare$	$SatStay$	-0.54
			Sun	-0.35

Table 7: OLS Regression Results for Model 0 (R^2 and Price Elasticity Estimate)

PoS	$MktSegType$	$SatStay$	R^2	$\hat{\beta}$
'A'	'EconAdvn'	0	0.204	0.102***
'A'	'EconAdvn'	1	0.370	0.380***
'A'	'EconLate'	0	0.472	0.472***
'A'	'EconLate'	1	0.556	0.382***
'A'	'FrstAdvn'	0	0.071	0.087***
'A'	'FrstAdvn'	1	0.124	0.066***
'A'	'FrstLate'	0	0.454	0.433***
'A'	'FrstLate'	1	0.350	0.219***
'D'	'EconAdvn'	0	0.233	0.121***
'D'	'EconAdvn'	1	0.353	0.205***
'D'	'EconLate'	0	0.438	0.407***
'D'	'EconLate'	1	0.526	-0.213***
'D'	'FrstAdvn'	0	0.153	NS
'D'	'FrstAdvn'	1	0.124	0.037**
'D'	'FrstLate'	0	0.407	0.380***
'D'	'FrstLate'	1	0.377	0.116***

**0.05 significance level
***<0.001 significance level
NS: Not significant

4.4 *Redefining the Regression Model Structure - Incorporating Endogeneity*

In this section, we redefine our model structure to help us better capture the dynamics of the problem and incorporate endogeneity. First, we consider the days left to departure component, which still brings considerable sparsity into the problem as it is not quite likely to observe ticket sales at every days left value, particularly when it is further out from the departure date. The reason that we desire to include this component is that it is the main driver of price variation. Prices for different product types are controlled via availability, i.e., opening and closing of different fare classes or buckets. Note that the rail operator in this study employs a nested bucket approach. In other words, closed buckets do not usually get re-opened and the order of closing starts from the lower level (lower fare) bucket. The revenue manager checks inventory at certain days left points and decides whether to close a lower level bucket given the current ticket sales and the protection levels for upper level (higher fare) buckets. This can also explain why we observe increasing average prices as it gets closer to the departure date. Those inventory check points are generally referred to as the "*inventory reading days*". Since reading days are the control points that result in the interaction between supply and demand through the revenue manager's decisions, we use reading days for creating days left intervals, and perform aggregation at the reading days level instead of at the days left level. We call this new variable "$RddIndex$". Figure 17 shows the mapping between $RddIndex$ and $DaysLeft$ values. For example, $RddIndex = 15$ covers the interval from 28 to 34 days left to departure, while $RddIndex = DaysLeft = 0$ corresponds to the departure date. It can be observed from Figure 17 that inventory reading days are less frequent when it is further away from the departure date, and become more frequent as it gets closer to the departure date converging to one-day intervals (days left values), which would correspond to checking inventory every day. Note that we combined $RddIndex = 1$ and $RddIndex = 0$ into $RddIndex = 1$ for $POS = $ 'D' as same day purchases were quite low as compared to purchases on the day prior to the departure date for return trips.

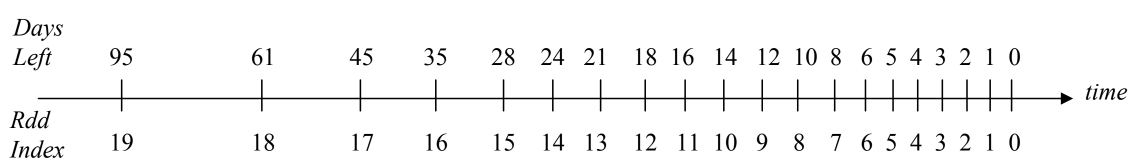


Figure 17: Mapping between $DaysLeft$ and $RddIndex$

One possible approach to control for the endogeneity in the data is the full-information approach, where the supply equation would be determined by the capacity allocation problem of the rail company. However, it is not straightforward to identify an accurate supply equation in this complex business environment. Moreover, as we discussed before, using an inaccurate supply equation may give inconsistent estimates while a limited information approach may still give consistent ones. Therefore, we employ the IV approach for this problem. The difficulty with the IV technique is that there is no global solution that applies to all industries and datasets [92, 121]. We choose to include the average prices lagged by reading days for each departure date and classification group as instruments. Thus, it is similar to the common usage of lagged prices as instruments in retail-based studies. However, we define the "lagging" according to the specifics of this environment, and expect the increase in the lagged average prices to give a signal of the inventory control decisions at each reading day, i.e., closing of lower fare buckets, implicitly providing a reason for increasing prices as it gets closer to the departure date. We call this new lagged average price variable "*lag_AvgFare*".

The other change that we make in our model is re-defining the price term as a ratio rather than an absolute value. Note that our regression model has time-related terms besides a price term, and we are interested in the percent change in demand for a percent change in price, i.e., the elasticity. If the rail operator had known the true "reference price" of customers and sold tickets only at that price, then, it would have observed some "reference demand", which would be due to factors other than price such as time, preference, etc. In [81], reference prices are defined as the standards against which the purchase price of a product is judged. Although it is not easy to find out the true reference price of customers, we use the median price paid in each classification group at each departure date as approximately reflective of the true reference price, "$RefPrice$", and we calculate the changes in demand relative to "reference" values. Thus, the reference price for advance purchasers would be different than that for late purchasers. We saw that such a "unitless" way of price measurement gives much better elasticity estimates than using the absolute values, as it also alleviates the impact of spurious price variation. We refer to these new price ratio variables as "*PRatio*" given by ($AvgFare/RefPrice$), and "*lag_PRatio*" given by ($lag\_AvgFare/RefPrice$).

Finally, similar to the creation of our lagged average prices, we also create a lagged variable for the number of tickets sold with respect to reading days considering that a linear relationship might not exist between *RddIndex* and *ln_Pax* in all cases, and the number of tickets sold at the previous reading day might give a better signal about the number of tickets sold on the current reading day. We call this new variable "*lag_Pax*". Given the definition of our lagged variables, the last reading day index at each departure date is dropped from the model since it does not have any prior observations. Our new regression model, Model 1, is given by Equation (30). Note that we also include $TimeSlot$ as a classification variable as we anticipate better fit for more popular time slots, which makes each classification group to be defined by PoS, $MktSegType$, $SatStay$ and $TimeSlot$.

$$\begin{aligned} ln\_Pax = \quad & ln(\alpha) + \beta(ln\_PRatio) + b_0(RddIndex) \\ & +b_1 Sun + \ldots + b_6 Sat + b_7 Jan + \ldots + b_{16} Dec \\ & +b_{17} PubHol + b_{18}(ln\_AvgConn) + b_{19}(ln\_lag\_Pax) \end{aligned} \tag{30}$$

In the 2SLS method, the first stage regression model for price includes all independent variables from Equation (30) and *ln_lag_PRatio* as instruments:

$$\begin{aligned} ln\_PRatio = \quad & ln(\theta) + \gamma(ln\_lag\_PRatio) + c_0(RddIndex) \\ & +c_1 Sun + \ldots + c_6 Sat + c_7 Jan + \ldots + c_{16} Dec \\ & +c_{17} PubHol + c_{18}(ln\_AvgConn) + c_{19}(ln\_lag\_Pax) \end{aligned} \tag{31}$$

The second stage regression model for demand replaces the *ln_PRatio* term in Equation (30) with the predicted value of *ln_PRatio* from Equation (31), which we refer to as "$FittedFare$". Section C.3 in the Appendix gives the significant Pearson correlation coefficients that are greater/less than +/-0.20 in the new model. It can be seen that the correlation between *ln_Pax* and $RddIndex$ is not as strong as the one between *ln_Pax* and $DaysLeft$, while that between *ln_Pax* and *ln_lag_Pax* is quite significant justifying our expectation for defining lagged ticket sales. Except for some late purchase groups, we drop $RddIndex$ from the demand model and use it as an extra instrument in the price model given the strong correlation between *ln_PRatio* and $RddIndex$, which also eliminates possible multicollinearity introduced by those variables in the demand model.

We initially ran a full model regression for estimation of price elasticities for Model 1 through the following procedure:

1. Run a full model regression (SAS Procedure: Proc Reg) for the OLS in Equation (30).

2. Run the first stage model in Equation (31).

3. Run the second stage model in Equation (30) including the residual from Equation (31) as an extra variable. Check for the significance of the residual variable. If significant, run the second stage model in Equation (30) with $FittedFare$ in place of ln_PRatio.

4. Check model diagnostics; particularly variance inflation factors of parameter estimates, VIF, for multi-collinearity and Durbin-Watson statistics for autocorrelation of residuals.

5. Confirm the significance of endogeneity through the Hausman-specification test (SAS Procedure: Proc Model).

6. If $RddIndex$ is only used as an instrument in the price equation, check the statistical significance of over-identification.

7. Run SAS Procedure: Proc Syslin for direct estimation of the 2SLS model in order to get correct standard error calculations for the parameter estimates.

Given that we have 10 monthly indicators and 6 daily indicators, our observations from the full model showed that several of the variables were not significant for either demand or price. Therefore, we decided to run a stepwise regression on the OLS in Step 1, and only use the significant variables from this estimation in the subsequent steps. We used a significance level of 0.10 for entry into and exit from the model. We also performed a comparison of these results with those from the full model to ensure that we were not excluding any variables that would have been significant in the price equation or the final demand equation. Note that we forced the price variable into the model as it is the main variable of main interest for its effect on demand, although it might turn out to be insignificant. In Appendix C, we provide the SAS output for the stepwise OLS regression and the 2SLS estimation from Proc Syslin for each classification group. We do not provide the results from the full model regression and the first stage regression due to space concerns, but they are available upon request.

Model diagnostics did not show any immediate problems. A common rule of thumb is to use $VIF > 4$ for parameter estimates as an indicator of multi-collinearity. The majority of the VIF values in our models was within the range of 1-2, and the maximum observed values were less than 4. A rule of thumb for detection of autocorrelation in the residuals from regression models is that the Durbin-Watson statistic should be between the values of 1.5 and 2.5. Although this statistic is argued to underestimate autocorrelation when lagged variables are present, we note that our definition of lagged variables makes them interdependent on the associated departure date but independent across departure dates. Thus, the Durbin-Watson statistic can still provide valuable results for our model. We checked the Durbin-Watson statistic up to 7 lags, and all values were between 1.5 and 2.5 with majority of the values being centered around 2. For further confirmation, we tested the results from SAS Procedure: Proc Autoreg against those from SAS Procedure: Proc Reg. We saw that even for autoregressive terms that were marked as significant, the coefficient values were small and the parameter estimates or the R^2 of the model were not highly affected. Thus, we decided not to include autoregressive terms. Finally, we tested heteroskedasticity through the White, Breusch and Pagan, and Brown and Forsythe tests. We could not reject the existence of heteroskedasticity in the data, however, its impact was reduced when the predicted versus residual values were analyzed by day of week. It was observed that the error distribution was more homogeneous for Friday and Saturday for outbound trips, and for Sunday and Monday for return trips. Thus, the heteroskedasticity was mostly caused by sparse ticket distribution and several single ticket sales at different reading days intervals for the other days of the week. We combined some of the intervals with single ticket sales, but did not change the current structure significantly as we did not want to affect the supply-demand dynamics that exist in the data. For specifics on these statistical tests, the reader is referred to [70]. In the following two sections, we provide a discussion on the estimation results for economy and first class purchases.

4.4.1 Analysis of the Results for the Economy Class

Table 8 provides a comparison of the price elasticity estimates obtained from the stepwise OLS regression and the 2SLS regression for each classification group for the economy class. For the majority of the cases, we can immediately observe from Table 8 the significant change in the price elasticities when endogeneity is accounted for. If endogeneity is not accounted for, one could end up with upward sloping demand curves (e.g., PoS=‘A’, $MktSegType$ =‘EconLate’, $SatStay = 0$), elastic curves incorrectly classified as inelastic curves (e.g., PoS=‘A’, $MktSegType$ =‘EconAdvn’, $SatStay = 1$), insignificant price terms (e.g., PoS=‘D’, $MktSegType$ =‘EconAdvn’, $SatStay = 0$) or under-estimated price elasticities (e.g., PoS=‘A’, $MktSegType$ =‘EconLate’, $SatStay = 1$, $TimeSlot$=1). For each of these regressions, the residual from the first stage model was significant in the stepwise OLS regression of the demand equation, and the Hausman specification test confirmed the presence of endogeneity (unless otherwise stated in the Appendix). For late purchases, we observed that some reading day intervals had considerably less or more sales as compared to the other intervals, which was not due to a change in price. For these cases, we included indicator variables for the specific interval ($RDD5$ would correspond to $RddIndex = 5$). We saw that there was a significant decrease in the number of tickets sold on the day of departure ($RDD0 = 1$), if the travel was for the early hours of the day ($TimeSlot = 1$). We can interpret this observation such that if passengers need to travel early, they do not delay purchasing the ticket until the departure date, not to risk the possibility of not finding a ticket on the train.

Table 8: Stepwise OLS vs. 2SLS Regression Results for Model 1 for the Economy Class (Adj. R^2 and Price Elasticity Estimate)

PoS	*MktSegType*	*Sat_Stay*	*Time_Slot*	OLS		2SLS	
				Adj. R^2	$\hat{\beta}$	Adj. R^2	$\hat{\beta}$
'A'	'EconAdvn'	1	1	0.781	-0.407***	0.748	-1.972***
'A'	'EconAdvn'	1	2	0.795	-0.630***	0.776	-2.002***
'A'	'EconAdvn'	1	3	0.719	-0.200**	0.670	-2.023***
'A'	'EconAdvn'	0	1	0.441	-0.403***	0.429	-1.106***
'A'	'EconAdvn'	0	2	0.415	-0.300***	0.373	-1.756***
'A'	'EconAdvn'	0	3	0.213	*NS*	0.211	*NS*
'A'	'EconLate'	1	1	0.685	*NS*	0.674	-0.674**
'A'	'EconLate'	1	2	0.719	*NS*	0.715	-0.472***
'A'	'EconLate'	1	3	0.592	*NS*	0.582	-0.709***
'A'	'EconLate'	0	1	0.411	0.660***	0.324	-1.012***
'A'	'EconLate'	0	2	0.374	0.468***	0.259	-2.080***
'A'	'EconLate'	0	3	0.448	0.550***	0.328	-1.435***
'D'	'EconAdvn'	1	1	0.719	-0.607***	0.663	-2.183***
'D'	'EconAdvn'	1	2	0.756	-0.709***	0.719	-2.107***
'D'	'EconAdvn'	0	1	0.392	*NS*	0.340	-0.983***
'D'	'EconAdvn'	0	2	0.521	*NS*	0.513	-0.358***
'D'	'EconLate'	1	1	0.656	-0.411***	0.638	-1.138***
'D'	'EconLate'	1	2	0.672	-0.831***	0.666	-1.238***
'D'	'EconLate'	0	1	0.190	0.096***	0.179	-0.267**
'D'	'EconLate'	0	2	0.402	0.594***	0.338	-0.282***

*0.10 significance level
**0.05 significance level
***<0.005 significance level
NS: Not significant

We can summarize our observations as follows:

- Advance purchasers with Saturday night stay constitute the most price sensitive market segment.
- Passengers with Saturday night stay are in general more price sensitive than the ones without Saturday night stay except for the outbound trip late purchases, which was

not anticipated. We can interpret this observation such that leisure travelers are less sensitive to the prices paid for last minute weekend trips to 'DEF'.

- Passengers from 'D' with Saturday night stay are slightly more price sensitive than those from 'A' for advance purchases; and significantly more price sensitive for late purchases. The business expectation was also in the direction of the customers from 'D' being more price sensitive. However, we see that the opposite holds when there is no Saturday night stay. We can interpret those purchases as of customers traveling mainly for business in the economy class; hence, being less price sensitive when it is a return trip from work to home.

- Contrary to the business expectation that outbound economy class travel would peak on weekends, we observe a peak on Thursdays, Fridays and Saturdays for purchasers with Saturday night stay, which would be leisure oriented, whereas the volume is higher during the initial days of the week for purchasers without Saturday night stay, which would be business oriented. For leisure travelers, we can be claim that "day-trips" are not as popular as "stay-away" trips for weekends; i.e., travelers are more inclined to spend at least a night when traveling from 'ABC' to 'DEF' for the week-end.

- As inbound trips are return trips to 'D', we observe a similar day of week behavior as in the case of outbound trips but in an opposite fashion. Sunday and Monday are the peak days for travelers with a Saturday night stay, which would be leisure oriented, whereas the volume is higher towards the end of the week (before Sunday) for purchasers without Saturday night stay, which would be business oriented.

- Departure month is not as strong a factor as the departure day of week. In general, we observe a consistent decrease in January.

- In general, there are no substantial differences between the price sensitivities with respect to time slots, although ‘Afternoon’ hours for outbound trips with no Saturday night stay look more popular and more price sensitive. Performing the analysis by time slots also helped us isolate the noisy effects from unpopular time slots such as the ‘Evening’ hours for advance purchases with no Saturday night stay for better estimation in more popular slots.

4.4.2 Analysis of the Results for the First Class

Table 9 provides a comparison of the price elasticity estimates obtained from the stepwise OLS regression and the 2SLS regression for each classification group for the first class. Overall, the explanatory power of the OLS models are lower and the results for the 2SLS are less strong for the first class as compared to those for the economy class. This observation is partly due to the relatively low volume in ticket sales, particularly for advance purchases for early hours of return trips, which introduces considerable sparsity into the problem. Moreover, for late purchases, we observed high ticket sales at some lower fare levels along with higher fare levels with respect to the reading day. Thus, our endogeneity approach of using the closing of lower fare buckets could not completely explain the relatively spontaneous ticket sales in the first class as compared to the economy class. Moreover, for some cases in advance purchases, the prices paid did not change considerably with respect to the reading day interval giving no clear signal of closing of lower fare buckets. However, we can still see for several classification groups that accounting for endogeneity can significantly change price elasticity estimates as compared to those that are obtained from OLS models. Note that the findings for the first class are very similar to those in the economy class such as advance purchases with Saturday night stay being the most price elastic market segment, and the day of week preferences. We can also observe for several classification groups that the economy class purchases are more price sensitive than the first class purchases.

Table 9: Stepwise OLS vs. 2SLS Regression Results for Model 1 for the First Class (Adj. R^2 and Price Elasticity Estimate)

PoS	*MktSegType*	*Sat_ Stay*	*Time_ Slot*	**OLS** Adj. R^2	**OLS** $\hat{\beta}$	**2SLS** Adj. R^2	**2SLS** $\hat{\beta}$
'A'	'FrstAdvn'	1	1	0.501	-0.326***	0.370	-2.453***
'A'	'FrstAdvn'	1	2	0.488	-0.422***	0.428	-1.793***
'A'	'FrstAdvn'	1	3	0.503	-0.351***	0.381	-2.246***
'A'	'FrstAdvn'	0	1	0.105	0.084*	0.098	-0.325*
'A'	'FrstAdvn'	0	2	0.306	0.103**	0.224	-1.199***
'A'	'FrstAdvn'	0	3	0.149	0.254***	0.088	1.380**
'A'	'FrstLate'	1	1	0.254	*NS*	0.247	-0.393**
'A'	'FrstLate'	1	2	0.325	*NS*	0.312	-0.527***
'A'	'FrstLate'	1	3	0.411	0.100**	0.409	*NS*
'A'	'FrstLate'	0	1	0.390	0.778***	0.257	-1.495**
'A'	'FrstLate'	0	2	0.371	0.374***	0.235	-1.389**
'A'	'FrstLate'	0	3	0.460	0.456***	0.328	*NS*
'D'	'FrstAdvn'	1	1	0.216	0.100*	0.208	*NS*
'D'	'FrstAdvn'	1	2	0.342	*NS*	0.256	-1.339**
'D'	'FrstAdvn'	0	1	0.082	*NS*	0.084	*NS*
'D'	'FrstAdvn'	0	2	0.274	*NS*	0.062	4.788**
'D'	'FrstLate'	1	1	0.298	0.151***	0.287	*NS*
'D'	'FrstLate'	1	2	0.557	0.324***	0.457	-0.931**
'D'	'FrstLate'	0	1	0.306	0.244***	0.192	*NS*
'D'	'FrstLate'	0	2	0.455	0.179***	0.439	-0.621**

*0.10 significance level
**0.05 significance level
***<0.005 significance level
NS: Not significant

4.5 Conclusions

In this study, we empirically demonstrated the presence of the endogeneity problem in a passenger travel context using data from an international high speed rail operator. In order to control for endogeneity, we used an instrumental variable approach via two stage least squares estimation. We showed that particularly for economy class purchases, if one does not account for endogeneity, price elasticities may induce an upward-sloping demand curve suggesting that high price produces high demand, or may be biased downward to the extent that elastic demand curves are incorrectly classified as inelastic.

CHAPTER V

CONCLUSIONS AND FUTURE WORK

In this thesis, we first studied a firm with two independent functions, marketing and production, which serves customer demand that is sensitive to both price and leadtime. Price and leadtime decisions are made by marketing and production, respectively. Production needs to satisfy a certain percentage of orders on time under limited capacity. In Chapter 2, we analyzed the types of inefficiencies that result from the decentralization of these two functions under a monopoly. In order to achieve coordination, we proposed a transfer price contract with bonus payments, where marketing pays production a transfer price per unit produced, and both departments receive a fraction of the total revenues generated as a bonus payment. We showed the existence of a unique transfer price for a given fraction of total revenues offered to marketing that achieves coordination as long as production receives a satisfactory incentive as a fraction of total revenues. Finally, we analyzed the optimal decisions and profit when production can choose the capacity level. A possible extension of this work would be generalizations to other queueing settings. It would also be interesting to study a Nash bargaining framework rather than a Stackelberg framework. Moreover, extensions to operational settings, such as a multi-period model, would be of interest, as the steady-state results (e.g., the service level constraint) would not always hold in the day-to-day operations of a firm.

In Chapter 3, we extended this work to a duopoly setting and analyzed the impact of the decentralization of price and lead-time decisions, when one or both firms compete with a decentralized organizational structure. We show the existence of a unique subgame perfect Nash Equilibrium under all outcomes from the first stage of the game, where organizational structures are determined. We observed that a firm's preference for a centralized or decentralized structure, given its competitor's structure, could change depending on market and firm characteristics. As an extension of this second study, one can compare the results of the linear demand model with a constant elasticity model to see how the decisions and the impact of decentralization change. Another extension would be including capacity as a decision variable. Finally, competition under dynamic price and lead-time quotations would also be of interest for future work.

In Chapter 4, we empirically demonstrated the presence of the endogeneity problem in a passenger travel context using data from an international high speed rail operator. We showed that if one does not account for endogeneity, price elasticities may induce an upward-sloping demand curve suggesting that high price produces high demand, or may be biased downward to the extent that elastic demand curves being incorrectly classified as inelastic. In order to control for endogeneity, we employed an instrumental variable approach and used the average prices lagged by "reading days", which are different days left points at which the observed demand is checked against inventory and lower fare buckets are closed as necessary, as instruments for each departure date and classification group. We were also interested in testing the "goodness" of the fare or level of the lowest fare bucket available (open) at each reading day as instruments. However, the inventory availability information in the current dataset was not complete, and missing values would have resulted in loss of half of the records. Thus, we decided to leave this for future research collecting a new, more complete dataset, and conducting a train-level analysis. With a new dataset that covers a longer period of time, we could also estimate seasonality through Fourier series and similar models, and compare the results against an indicator variable approach, which becomes the most convenient way to model time-related effects when less than a year of data is available as it was the case in this study. A final note on Chapter 4 is that although we did not have a capacity issue with our current dataset, in general, given the capacity of a train and the availability controls of inventory, what is observed about the customer demand would be the number of tickets sold and not the true underlying demand. This problem would fall under the general class of censored models with limited dependent variables. The analysis and estimation of possible modeling approaches as described in [77] are left for future research.

APPENDIX A

ADDENDUM FOR CHAPTER 2

A.1 PROOF OF PROPOSITION 1

As in [95], Constraint (2) is tight at optimality. Thus, it is sufficient to treat two of the three variables, p_c, L_c, and λ_c as decision variables and determine the other variable via the equality, $\lambda_c = D(p_c, L_c)$. We choose to eliminate price from this formulation for computational simplicity. Moreover, since Constraint (1) can be rewritten as $(\mu - \lambda_c)L_c \geq \ln(1/(1-s))$, denoting $\ln(1/(1-s))$ by k we get the following formulation:

$$\max_{(\lambda_C, L_C) \geq 0} \quad \pi_c = \lambda_c(a - cL_c - \lambda_c - mb)/b$$
$$s.t. \quad (\mu - \lambda_c)L_c \geq k$$

Note that the stability condition $\lambda_c \leq \mu$ is implied by the service constraint since $k \geq 0$ and $L_c \geq 0$. The service constraint must be binding at optimality as in [95] and [114], since the objective function is linearly decreasing in L_c, and the minimum possible lead-time is defined by the boundary of the service constraint. Hence the optimal lead-time is:

$$L_c^* = \frac{k}{\mu - \lambda_c^*}$$

Substituting L_c^* into π_c gives an unconstrained optimization problem. First order conditions (FOC) provide Equation (4) for λ_c^*. To show uniqueness, note that

$$\frac{\partial f_c(\lambda_c)}{\partial \lambda_c} = -2(\mu - \lambda_c)^2 - 2(a - 2\lambda_c - mb)(\mu - \lambda_c) < 0$$

since $(\mu - \lambda_c) > 0$ on the interval $[0, \mu]$ and $(a - 2\lambda_c - mb) > 0$ by Equation (4) for the objective function to have a maximizer. This implies that $f_c(\lambda_c)$ is decreasing. Thus, if $f_c(\lambda_c)$ has a root on the interval $[0, \mu]$, then it will give the unique optimal arrival rate, λ_c^* for the centralized problem. Noting that $f_c(\mu) = -ck\mu < 0$, we also need $f_c(0) =$

$(a - mb)\mu^2 - ck\mu > 0$ for the existence of a root on $[0, \mu]$, which holds due to Assumption A3.

Second order conditions ensure that the root of Equation (4) is a global maximum, since the objective function is concave in λ_C. The optimal price p_C^* can then be obtained by rearranging terms in $\lambda_C^* = D(p_C^*, L_C^*)$. ■

A.2 PROOF OF PROPOSITION 2

In order for $p_P^*(L_P) = \frac{a-cL_P}{2b}$, we should have $\frac{a-cL_P}{2b} \leq m$ or equivalently, $L_P \leq \frac{a-2mb}{c}$. Thus, we first need $a - 2mb > 0$. Let's assume that $p_P^*(L_P) = \frac{a-cL_P}{2b}$. Then, let y_P^1 and y_P^2 be the roots of Constraint (7) when it is binding, i.e., $\left(\mu - \frac{a-cL_P}{2}\right) L_P = k$. The positive root, y_P^1 is given by

$$y_P^1 = \frac{(a - 2\mu) + \sqrt{(2\mu - a)^2 + 8ck}}{2c}$$

Hence, in a feasible solution, $L_P \in [y_P^1, \frac{a}{c}]$ since demand is downward sloping in L_P, and is zero at $\frac{a}{c}$. Note that we have $y_P^1 \leq \frac{a}{c}$ if and only if $\mu \geq \frac{ck}{a}$, which holds under Assumption A3. Since the objective function is convex, the optimal solution lies on the boundaries of the interval $[y_P^1, \frac{a}{c}]$. Let x_P^1 and x_P^2 be the roots of the objective function, π_P^{PR}, where $x_P^1 = \frac{a}{c}$ and $x_P^2 = \frac{a-2mb}{c}$. Figure 18 shows an illustration of π_P^{PR} for $a-2mb > 0$. We need $y_P^1 < x_P^2$ for generating positive profits, which only holds if $\mu > bm + \frac{ck}{a-2mb}$. Note that if $a - 2mb \leq 0$ and/or $x_P^2 \leq y_P^1 \leq x_P^1$, then, y_P^1 generates zero or negative profits, so the optimal price would be constrained to the unit production cost, m, and the optimal lead-time, which lies on the boundary of Constraint (7), would be given by $\frac{a-bm-\mu+\sqrt{(\mu-a+bm)^2+4ck}}{2c}$. ■

A.3 PROOF OF PROPOSITION 3

FOC for π_M^{MR} give:

$$g(p_M) = \frac{\partial \pi_M^{MR}}{\partial p_M} = \frac{1}{2}\left[a + \mu - 2bp_M^0 - \frac{(a - bp_M^0 - \mu)(a - 2bp_M^0 - \mu) + 4ck}{\sqrt{(a - bp_M^0 - \mu)^2 + 4ck}}\right] = 0$$

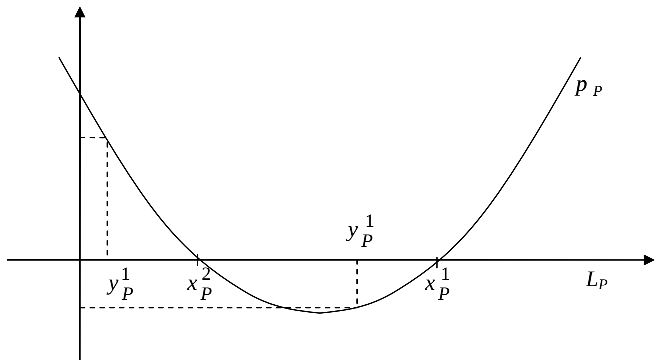


Figure 18: Illustration of case-(ii)

The optimal price is given by $p^*_M = \max\{p^0_M, m\}$, where p^0_M is the unique maximizer of π^{MR}_M over the interval $p_M \in [0, (a\mu - ck)/b\mu]$. Concavity of π^{MR}_M can be shown from the second order conditions:

$$\frac{\partial^2 \pi^{MR}_M}{\partial p^2_M} = -b\left[1 - \frac{(a - bp^0_M - \mu)}{\sqrt{(a - bp^0_M - \mu)^2 + 4ck}} + \frac{2ckbp^0_M}{\sqrt{(a - bp^0_M - \mu)^2 + 4ck}}\right] < 0$$

Moreover, $g(0) = \frac{1}{2}\left[a + \mu - \sqrt{(a-\mu)^2 + 4ck}\right] > 0$ and $g(\frac{a\mu - ck}{b\mu}) = -\mu\left[\frac{a\mu - ck}{ck + \mu^2}\right] < 0$ as $a > ck/\mu$ from Assumption A3. Therefore, p^0_M is the unique maximizer of π^{MR}_M over $[0, \frac{a\mu - ck}{b\mu}]$. FOC for π^{MR}_M with a change of variables give Equation (11). ■

A.4 PROOF OF PROPOSITION 4

$f_M(.)$ is decreasing and convex on the interval $[0, \mu]$. Since

$$f_M(\lambda^*_P) = -\tfrac{1}{4}ck\left(a + 2\mu - \sqrt{(a - 2\mu)^2 + 8ck}\right) < 0$$

it follows that $\lambda^*_P > \lambda^*_M$ except when $\max\{p^*_P, m\} = m$ and $\max\{p^*_M, m\} = m$ in which case $\lambda^*_P = \lambda^*_M$. For the centralized setting, combining Equations (4) and (11), we can write

$$\frac{a - 2\lambda^*_C - mb}{a - 2\lambda^*_M} = \frac{(\mu - \lambda^*_M)^2}{(\mu - \lambda^*_C)^2}$$

which gives $\lambda^*_C < \lambda^*_M$. The results for lead-times and prices follow from the fact that the former increases and the latter decreases in the demand generated as $L^*_. = \frac{k}{\mu - \lambda^*_.}$ and

$p_\cdot = \frac{a-\lambda_\cdot - \frac{ck}{\mu-\lambda_\cdot}}{b}$. Note that since $p_C^* > m$, which holds through Assumption A3, we do not have equalities between the decisions of the centralized and the decentralized settings.

As for the comparison of profits, we find the profit difference between C and M as:

$$\begin{aligned}
\pi_C^* - \pi_M^* &= \left(p_C^* - m\right)\lambda_C^* - \left(p_M^* - m\right)\lambda_M^* \\
&= \frac{a}{b}\left(\lambda_C^* - \lambda_M^*\right) - \frac{1}{b}\left((\lambda_C^*)^2 - (\lambda_M^*)^2\right) - \frac{1}{b}ck\mu\frac{\left(\lambda_C^* - \lambda_M^*\right)}{\left(\mu - \lambda_C^*\right)\left(\mu - \lambda_M^*\right)} - m\left(\lambda_C^* - \lambda_M^*\right)
\end{aligned}$$

Since $\lambda_M^* > \lambda_C^*$, $\mu > \lambda_M^*$ and $\mu > \lambda_C^*$, the first term of this equation is negative, while the other three terms are positive. Therefore, we need to examine the relation between these terms in more detail. From Equation (4), if we replace $ck\mu$ with $\left(a - 2\lambda_C^* - mb\right)\left(\mu - \lambda_C^*\right)^2$, after simplification, the profit difference becomes:

$$\begin{aligned}
\pi_C^* - \pi_M^* = \frac{a}{b}\left(\lambda_C^* - \lambda_M^*\right) - \frac{1}{b}\left((\lambda_C^*)^2 - (\lambda_M^*)^2\right) - m\left(\lambda_C^* - \lambda_M^*\right) \\
-\frac{1}{b}\left(a - 2\lambda_C^* - mb\right)\left(\mu - \lambda_C^*\right)\frac{\left(\lambda_C^* - \lambda_M^*\right)}{\left(\mu - \lambda_M^*\right)} \\
= \frac{\left(\lambda_C^* - \lambda_M^*\right)}{b}\left[\left(a - (\lambda_C^* + \lambda_M^*) - mb\right) - \left(a - 2\lambda_C^* - mb\right)\frac{\left(\mu - \lambda_C^*\right)}{\left(\mu - \lambda_M^*\right)}\right] \qquad (32)
\end{aligned}$$

The first term of Equation (32) is negative, while the term in brackets is negative since $\left(a - (\lambda_C^* + \lambda_M^*) - mb\right) < \left(a - 2\lambda_C^* - mb\right)$, while $\left(\mu - \lambda_C^*\right) > \left(\mu - \lambda_M^*\right)$. Hence, we conclude that $\pi_C^* - \pi_M^* > 0$. The profit difference between M and P is:

$$\begin{aligned}
\pi_M^* - \pi_P^* &= \left(p_M^* - m\right)\lambda_M^* - \left(p_P^* - m\right)\lambda_P^* \\
&= \frac{a}{b}\left(\lambda_M^* - \lambda_P^*\right) - \frac{1}{b}\left((\lambda_M^*)^2 - (\lambda_P^*)^2\right) - \frac{1}{b}ck\mu\frac{\left(\lambda_M^* - \lambda_P^*\right)}{\left(\mu - \lambda_M^*\right)\left(\mu - \lambda_P^*\right)} - m\left(\lambda_M^* - \lambda_P^*\right)
\end{aligned}$$

From Equation (11) we replace $ck\mu$ with $\left(a-2\lambda^*_M\right)\left(\mu-\lambda^*_M\right)^2$:

$$\begin{aligned}\pi^*_M-\pi^*_P &= \frac{a}{b}\left(\lambda^*_M-\lambda^*_P\right)-\frac{1}{b}\left((\lambda^*_M)^2-(\lambda^*_P)^2\right)-m\left(\lambda^*_M-\lambda^*_P\right)\\ &\qquad -\frac{1}{b}\left(a-2\lambda^*_M\right)\left(\mu-\lambda^*_M\right)\frac{\left(\lambda^*_M-\lambda^*_P\right)}{\left(\mu-\lambda^*_P\right)}\\ &= \frac{\left(\lambda^*_M-\lambda^*_P\right)}{b}\left[\left(a-(\lambda^*_M+\lambda^*_P)-mb\right)-\left(a-2\lambda^*_M\right)\frac{\left(\mu-\lambda^*_M\right)}{\left(\mu-\lambda^*_P\right)}\right] \end{aligned} \tag{33}$$

The first term of Equation (33) is non-positive, while the term in brackets is negative since $\left(a-(\lambda^*_M+\lambda^*_P)-mb\right) < \left(a-2\lambda^*_M\right)$, while $\left(\mu-\lambda^*_M\right) \geq \left(\mu-\lambda^*_P\right)$. Hence, we conclude that $\pi^*_M-\pi^*_P \geq 0$. ■

A.5 PROOF OF PROPOSITION 5

Let $R(.)$ denote revenue. The positive revenue difference between M and P ($R(M)-R(P) > 0$) directly follows from the proof of Proposition 4, where $\pi^*_M-\pi^*_P \geq 0$ with $m = 0$. As for the comparison of revenues under C and M, we change the proof for profits slightly:

$$\begin{aligned}R(C)-R(M) &= p^*_C\lambda^*_C - p^*_M\lambda^*_M\\ &= \frac{a}{b}\left(\lambda^*_C-\lambda^*_M\right)-\frac{1}{b}\left((\lambda^*_C)^2-(\lambda^*_M)^2\right)-\frac{1}{b}ck\mu\frac{\left(\lambda^*_C-\lambda^*_M\right)}{\left(\mu-\lambda^*_C\right)\left(\mu-\lambda^*_M\right)}\end{aligned}$$

From Equation (11), if we replace $ck\mu$ with $\left(a-2\lambda^*_M\right)\left(\mu-\lambda^*_M\right)^2$, after simplification, the revenue difference becomes:

$$\begin{aligned}R(C)-R(M) &= \frac{a}{b}\left(\lambda^*_C-\lambda^*_M\right)-\frac{1}{b}\left((\lambda^*_C)^2-(\lambda^*_M)^2\right)-\frac{1}{b}\left(a-2\lambda^*_M\right)\left(\mu-\lambda^*_M\right)\frac{\left(\lambda^*_C-\lambda^*_M\right)}{\left(\mu-\lambda^*_C\right)}\\ &= \frac{\left(\lambda^*_C-\lambda^*_M\right)}{b}\left[\left(a-(\lambda^*_C+\lambda^*_M)\right)-\left(a-2\lambda^*_M\right)\frac{\left(\mu-\lambda^*_M\right)}{\left(\mu-\lambda^*_C\right)}\right]\end{aligned} \tag{34}$$

The first term of Equation (34) is negative, while the term in brackets is positive as $\left(a-(\lambda^*_C+\lambda^*_M)\right) > 0$ and $\frac{\left(a-(\lambda^*_C+\lambda^*_M)\right)}{\left(a-2\lambda^*_M\right)} > 1$, while $\frac{\left(\mu-\lambda^*_M\right)}{\left(\mu-\lambda^*_C\right)} < 1$. Hence, we conclude that $R(M)-R(C) > 0$. ■

A.6 SENSITIVITY ANALYSIS FOR OPTIMAL DECISIONS

We first provide an example for the centralized setting, namely the derivation of the change in λ_C^* with respect to μ.

$$\frac{\partial \lambda_C^*}{\partial \mu} = -\frac{ck - 2(\mu - \lambda_C^*)(a - mb - 2\lambda_C^*)}{2(\mu - \lambda_C^*)[(\mu - \lambda_C^*) + (a - mb - 2\lambda_C^*)]} \tag{35}$$

It can be seen from Equation (4) that $(a - 2\lambda_C^* - mb) \geq 0$ since the right hand side and $(\mu - \lambda_C^*)^2$ are positive. We also know that $(\mu - \lambda_C^*) \geq 0$ for the stability condition to hold. Hence, the denominator of Equation (35) is positive. From Equation (4) it follows that $(a - 2\lambda_C^* - mb) = \frac{ck\mu}{(\mu - \lambda_C^*)^2}$, and we obtain:

$$\begin{aligned}
\frac{\partial \lambda_C^*}{\partial \mu} &= \frac{-\left(ck - 2(\mu - \lambda_C^*)\frac{ck\mu}{(\mu - \lambda_C^*)^2}\right)}{2(\mu - \lambda_C^*)[(\mu - \lambda_C^*) + (a - mb - 2\lambda_C^*)]} \\
&= \frac{-ck\left((\mu - \lambda_C^*) - 2\mu\right)}{2(\mu - \lambda_C^*)^2[(\mu - \lambda_C^*) + (a - mb - 2\lambda_C^*)]} \geq 0 \ \ (\text{since } (-\lambda_C^* - \mu) \leq 0)
\end{aligned}$$

Therefore, the optimal demand rate for the centralized system is increasing in capacity. In order to see the effect of capacity on the optimal lead-time, we use that $L_C^* = \frac{k}{\mu - \lambda_C^*}$.

$$\begin{aligned}
\frac{\partial L_C^*}{\partial \mu} &= -\frac{k}{\left(\mu - \lambda_C^*\right)^2}\left(1 - \frac{\partial \lambda_C^*}{\partial \mu}\right) \\
&= -\frac{2k\left(\mu - \lambda_C^*\right)^2 + ck^2}{2\left(\mu - \lambda_C^*\right)^3\left[\left(\mu - \lambda_C^*\right) + \left(a - mb - 2\lambda_C^*\right)\right]} \leq 0
\end{aligned}$$

So, optimal lead-time for the centralized system is decreasing in capacity.

We next give an example for the decentralized setting, P. For simplicity, we choose the change with respect to the price sensitivity of demand, b.

$$\begin{aligned}
L_P^* &= \frac{(a - 2\mu) + \sqrt{(2\mu - a)^2 + 8ck}}{2c} \quad \Rightarrow \quad \frac{\partial L_P^*}{\partial b} = 0 \\
p_P^* &= \frac{a - cL_P^*}{2b} \quad \Rightarrow \quad \frac{\partial p_P^*}{\partial b} = -\frac{a}{2b^2} \leq 0 \\
\lambda_P^* &= \frac{a - cL_P^*}{2} \quad \Rightarrow \quad \frac{\partial \lambda_P^*}{\partial b} = 0
\end{aligned}$$

For this case, optimal price is decreasing in price sensitivity, while optimal lead-time and optimal demand rate are not affected. The other entries of Table 1 have been developed similarly.

Table 10: Partial derivatives of the optimal demand and price for the centralized setting

	$\partial\lambda_C^*/$	$\partial p_C^*/$
∂a	$\frac{\mu-\lambda_C^*}{2[(\mu-\lambda_C^*)+(a-mb-2\lambda_C^*)]} \geq 0$	$\frac{(\mu-\lambda_C^*)+2(\mu-\lambda_C^*)(a-mb-2\lambda_C^*)-ck}{2b(\mu-\lambda_C^*)[(\mu-\lambda_C^*)+(a-mb-2\lambda_C^*)]} \geq 0$
∂b	$-m\frac{\mu-\lambda_C^*}{2[(\mu-\lambda_C^*)+(a-mb-2\lambda_C^*)]} \leq 0$	$\frac{m}{2}\frac{(\mu-\lambda_C^*)^2+ck}{(\mu-\lambda_C^*)[(\mu-\lambda_C^*)+(a-mb-2\lambda_C^*)]b} - \frac{(\mu-\lambda_C^*)(a-\lambda_C^*)-ck}{(\mu-\lambda_C^*)b^2}$
∂c	$-\frac{k\mu}{2(\mu-\lambda_C^*)[(\mu-\lambda_C^*)+(a-mb-2\lambda_C^*)]} \leq 0$	$-\frac{k}{2}\frac{(\mu-\lambda_C^*)^2(a-mb-4\lambda_C^*+\mu)}{(\mu-\lambda_C^*)^3[(\mu-\lambda_C^*)+(a-mb-2\lambda_C^*)]b}$
∂m	$-b\frac{\mu-\lambda_C^*}{2[(\mu-\lambda_C^*)+(a-mb-2\lambda_C^*)]} \leq 0$	≥ 0 (as $p_C^* = \frac{a-\lambda_C^*-cL_C^*}{b}$)
∂k	$-\frac{c\mu}{2[(\mu-\lambda_C^*)+(a-mb-2\lambda_C^*)]} \leq 0$	$-\frac{c}{2}\frac{(\mu-\lambda_C^*)^2(a-mb-4\lambda_C^*+\mu)}{(\mu-\lambda_C^*)^3[(\mu-\lambda_C^*)+(a-mb-2\lambda_C^*)]b}$
$\partial\mu$	$-\frac{ck-2(\mu-\lambda_C^*)(a-mb-2\lambda_C^*)}{2(\mu-\lambda_C^*)[(\mu-\lambda_C^*)+(a-mb-2\lambda_C^*)]} \geq 0$	$\frac{5ck(\mu-\lambda_C^*)^2-2(\mu-\lambda_C^*)ck\mu+2c^2k^2}{(\mu-\lambda_C^*)^3[(\mu-\lambda_C^*)+(a-mb-2\lambda_C^*)]b}$

For L_C^*, the results with respect to a, b, c, m directly follow from $L_C^* = \frac{k}{\mu-\lambda_C^*}$, and with respect to k, $\frac{\partial L_C^*}{\partial k} = \frac{2(\mu-\lambda_C^*)^2[(\mu-\lambda_C^*)+(a-mb-2\lambda_C^*)]-ck\mu}{2(\mu-\lambda_C^*)^3[(\mu-\lambda_C^*)+(a-mb-2\lambda_C^*)]} \geq 0$. ■

Table 11: Partial derivatives of the optimal demand and price for the decentralized setting P

	$\partial L_P^*/$	$\partial\lambda_P^*/$	$\partial p_P^*/$
∂a	$-\frac{a-2\mu-\sqrt{(2\mu-a)^2+8ck}}{2c\sqrt{(2\mu-a)^2+8ck}} \geq 0$	$\frac{2\mu-a+\sqrt{(2\mu-a)^2+8ck}}{4\sqrt{(2\mu-a)^2+8ck}} \geq 0$	$\frac{2\mu-a+\sqrt{(2\mu-a)^2+8ck}}{4b\sqrt{(2\mu-a)^2+8ck}} \geq 0$
∂b	0	0	$-\frac{2\mu+a-\sqrt{(2\mu-a)^2+8ck}}{4b^2} \leq 0$
∂c	$-\frac{4ck+\left((2\mu-a)^2-(2\mu-a)\sqrt{(2\mu-a)^2+8ck}\right)}{2c^2\sqrt{(2\mu-a)^2+8ck}} \leq 0$	$-\frac{k}{\sqrt{(2\mu-a)^2+8ck}} \leq 0$	$-\frac{k}{b\sqrt{(2\mu-a)^2+8ck}} \leq 0$
∂m	0	0	0
∂k	$\frac{2}{\sqrt{(2\mu-a)^2+8ck}} \geq 0$	≤ 0 (as $\lambda_{D_0}^* = \frac{a-cL_{D_0}^*}{2}$)	≤ 0 (as $p_{D_0}^* = \frac{a-cL_{D_0}^*}{2b}$)
$\partial\mu$	$\frac{2\mu-a-\sqrt{(2\mu-a)^2+8ck}}{c\sqrt{(2\mu-a)^2+8ck}} \leq 0$	≥ 0 (as $\lambda_{D_0}^* = \frac{a-cL_{D_0}^*}{2}$)	≥ 0 (as $\lambda_{D_0}^* = \frac{a-cL_{D_0}^*}{2}$)

A.7 PROOF OF PROPOSITION 6

Let $x_C = mb$ and $x_M = 0$, and $i = C,\ M$. Then, the following analysis will hold for both settings. The change in p_i^* with respect to c is:

$$\frac{\partial p_i^*}{\partial c} = -\frac{k}{2b}\frac{(a - x_i - 4\lambda_i^* + \mu)}{(\mu - \lambda_i^*)[(\mu - \lambda_i^*) + (a - x_i - 2\lambda_i^*)]}$$

If $(a-x_i-4\lambda_i^*+\mu) < 0$, then p_i^* is increasing in c. If $(a-x_i-4\lambda_i^*+\mu) > 0$, then $\frac{\partial p_i^*}{\partial c} < 0$ and p_i^* is decreasing in c, which is satisfied when $f_i\left(\frac{1}{4}(a-x_i+\mu)\right) < 0$, since $f_i(\lambda_i)$ is decreasing in λ_i on $[0,\mu]$. Note that if $\frac{1}{4}(a-x_i+\mu) > \mu$, then since $\lambda_i^* \leq \mu$, p_i^* will be decreasing in c. Thus, c_i^0 is given as the c, which sets Equation (36) to 0.

$$f_i\left(\frac{1}{4}(a-x_i+\mu)\right) = \left(\frac{a-x_i-\mu}{2}\right)\left(\frac{a-x_i-3\mu}{4}\right)^2 - ck\mu \tag{36}$$

Note that $f_i(.) < 0$ when $\mu > a - x_i$ as seen from Equation (36). Similarly, for the change in p_i^* with respect to s:

$$\frac{\partial p_i^*}{\partial k} = -\frac{c}{2b}\frac{(a-x_i-4\lambda_i^*+\mu)}{(\mu-\lambda_i^*)[(\mu-\lambda_i^*)+(a-x_i-2\lambda_i^*)]} \tag{37}$$

The sign of this equation also depends on $(a-x_i-4\lambda_i^*+\mu)$. Therefore, when $\lambda_i^* < \frac{1}{4}(a-x_i+\mu)$, we obtain the same capacity interval for each related setting, and s_i^0 and k_i^0 are given by the k, which sets Equation (37) to 0. ■

A.8 PROOF OF PROPOSITION 7

We first analyze the problems of marketing and production under P. We start with marketing's problem and find its best response as:

$$p_P^*(L_P) = \left[\frac{a-cL_P}{2b} + \frac{w}{2\alpha_1}\right]^+ \text{ and } \lambda_P^*(L_P) = \left[\frac{a-cL_P}{2} - \frac{wb}{2\alpha_1}\right]^+$$

Production's problem is:

$$\begin{aligned} \max_{(0\leq L_P \leq \frac{a}{c}-\frac{wb}{c\alpha_1})} \quad \pi_P^{PR} &= (w-m)\lambda_P^*(L_P) + \alpha_2 p_P^*(L_P)\lambda_P^*(L_P) && (38)\\ &= (w-m)\left(\frac{a-cL_P}{2} - \frac{wb}{2\alpha_1}\right) + \alpha_2 b\left(\left(\frac{a-cL_P}{2b}\right)^2 - \frac{w^2}{4(\alpha_1)^2}\right) \\ s.t. \quad \left(\mu - \frac{a-cL_P}{2} + \frac{wb}{2\alpha_1}\right) L_P &\geq k && (39)\end{aligned}$$

Note that $L_P \leq \frac{a}{c} - \frac{wb}{c\alpha_1}$ ensures positive margin for marketing and positive demand. Let y_P^1 be the positive root of Constraint (39) when it is binding:

$$y_P^1 = \frac{a-2\mu-wb/\alpha_1 + \sqrt{(a-2\mu-wb/\alpha_1)^2+8ck}}{2c}$$

The two roots of π_P^{PR} are given by $x_P^1 = \left(\frac{a}{c} - \frac{wb}{c\alpha_1}\right)$ and $x_P^2 = \frac{a}{c} + \frac{wb}{c\alpha_1} - 2\frac{(m-w)b}{c\alpha_2}$. The feasible region is defined by $[y_P^1, x_P^1]$, and for feasibility, it should hold that $y_P^1 \leq x_P^1 = \frac{a}{c} - \frac{wb}{c\alpha_1}$, which is satisfied if $w \leq \alpha_1\left(\frac{a}{b} - \frac{ck}{\mu b}\right)$. As long as $\alpha_2 \geq 0$, π_P^{PR} is convex, and the optimal solution lies on the boundaries of $[y_P^1, x_P^1]$. The optimal lead-time is determined as follows:

(i) $x_P^1 > x_P^2 \Leftrightarrow w < \frac{\alpha_1 m}{\alpha_1+\alpha_2}$: If $y_P^1 < x_P^2$, then $L_P^* = y_P^1$ and $\pi_P^{PR} > 0$; otherwise, $L_P^* = x_P^1$ and $\pi_P^{PR} = 0$.

(ii) $x_P^1 \leq x_P^2 \Leftrightarrow w \geq \frac{\alpha_1 m}{\alpha_1+\alpha_2}$: $L_P^* = y_P^1$ and $\pi_P^{PR} > 0$.

Case (i) is developed similar to the proof of Proposition 2, and case (ii) is trivial. If $w \geq m$, production will have a positive margin, i.e., $\alpha_2 p_P^* + w - m \geq 0$, for any $\alpha_2 \geq 0$. In other words, production does not require a fraction of the revenues as long as the transfer price paid by marketing covers the production costs. Otherwise, the minimum α_2 that achieves $L_P^* = y_P^1$ is given by the value which satisfies $y_M^1 < x_M^2$ in case (i):

$$\alpha_{2P}^{min}(\alpha_1, w) = \max\left\{\frac{4b(m-w)}{a + 2\mu + 3wb/\alpha_1 - \sqrt{(a - 2\mu - wb/\alpha_1)^2 + 8ck}}, 0\right\}$$

As the maximum fraction of revenue that can be offered to production is $1 - \alpha_1$, we should guarantee $\alpha_{2P}^{min}(\alpha_1, w) \leq (1 - \alpha_1)$ by choosing a transfer price, $w \geq w_P^{min}$:

$$w_P^{min} = \max\left\{\frac{\alpha_1\left(\alpha_1(\alpha_1\mu+a+bm)+3bm-\mu-a+(1-\alpha_1)\sqrt{(\mu\alpha_1-a+bm+\mu)^2+4ck(1+\alpha_1)}\right)}{2b(1+\alpha_1)}, 0\right\}$$

For the (α_1, α_2, w) combinations stated in Proposition 7, the optimal solution for Model P is given by $L_P^* = y_P^1$, $p_P^* = p_P^*(L_P^*)$ and $\lambda_P^* = \lambda_P^*(L_P^*)$.

We next analyze the Marketing-Stackelberg game, M. As long as $\alpha_2 p_M^* + w - m \geq 0$, the service level constraint will be tight at optimality and the best response of production will be given by Equation (10):

$$L_M^*(p_M) = \frac{(a - bp_M - \mu) + \sqrt{(a - bp_M - \mu)^2 + 4ck}}{2c}$$

We prefer to solve marketing's problem in terms of λ_M^* and employ a change of variables. In this case, $L_M^*(\lambda_M) = k/(\mu - \lambda_M)$. Marketing's problem is then given by

$$\max_{(0 \le \lambda_M \le \mu)} \pi_M^{MR} = \left(\alpha_1 \frac{a - \lambda_M - \frac{ck}{\mu - \lambda_M}}{b} - w \right) \lambda_M$$

FOC give Equation (13) after rearranging terms. As $f_M(\mu) = -ck\mu < 0$, we desire to have $f_M(0) = (a - wb/\alpha_1)\mu^2 - ck\mu > 0$, and thus, we restrict our attention to $w \le \alpha_1 \left(\frac{a}{b} - \frac{ck}{\mu b} \right)$. Now that $f_M(.)$ has a root over $[0, \mu]$, it should hold that $(a - 2\lambda_M^* - wb/\alpha_1) > 0$. Uniqueness is guaranteed as $f_M(.)$ is decreasing over $[0, \mu]$:

$$\frac{\partial f_M(\lambda_M)}{\partial \lambda_M} = -2(\mu - \lambda_M)^2 - 2(a - 2\lambda_M - wb/\alpha_1)(\mu - \lambda_M) < 0$$

We can check that the margin for marketing is positive, i.e., $\alpha_1 p_M^* - w \ge 0$ from the optimality equation.

$$\begin{aligned} &a - \lambda_M^* - wb/\alpha_1 > a - 2\lambda_M^* - wb/\alpha_1 = \frac{ck\mu}{(\mu - \lambda_M^*)^2} > \frac{ck}{\mu - \lambda_M^*} \\ &\Rightarrow a - \lambda_M^* - \frac{ck}{\mu - \lambda_M^*} > wb/\alpha_1 \Rightarrow p_M^* > w/\alpha_1 \quad \surd \end{aligned}$$

We also need to provide a positive margin to production for optimality, i.e., $\alpha_2 p_M + w - m \ge 0$. Note that this margin is positive for all $\alpha_2 \ge 0$ if $w \ge m$. When $w < m$, we need to solve $\alpha_2(a - \lambda_M - \frac{ck}{\mu - \lambda_M}) + (w - m)b = 0$ for λ_M. The root that falls in $[0, \mu]$ is given by:

$$\lambda_M^0(\alpha_2) = \frac{1}{2\alpha_2} \left(\alpha_2(\mu + a) - (m - w)b - \sqrt{(-\alpha_2(\mu - a) - b(m - w))^2 + 4\alpha_2^2 ck} \right) \tag{40}$$

Thus, $\alpha_{2M}^{min}(\alpha_1, w)$ is equal to the α_2 value that sets $f_M(\lambda_M^0(\alpha_2)) = 0$ for $w < m$ and 0 for $w \ge m$. We also need to find the minimum transfer price for a given α_1 that will ensure $\alpha_2 \le 1 - \alpha_1$. If we solve $(1 - \alpha_1)p_M + w - m = 0$ for λ_M, we will obtain Equation (40) with $\alpha_2 = 1 - \alpha_1$, i.e., $\lambda_M^0(w)$. Then, $w_M^{min}(\alpha_1)$ will be equal to the maximum of 0 and the w value that sets $f_M(\lambda_M^0(w)) = 0$. ■

A.9 PROOF OF PROPOSITION 8

For the (α_1, α_2, w) combinations stated in Proposition 7, the service level constraints will be tight at optimality for all settings. Then, choosing the contract parameters such that

$\lambda_i^* = \lambda_C^*,\ i = P, M$ is sufficient to achieve coordination as $L_\cdot^* = \frac{k}{\mu-\lambda_\cdot^*}$ and $p_\cdot^* = \frac{a-\lambda_\cdot^*-\frac{ck}{\mu-\lambda_\cdot^*}}{b}$. Thus, we only need to ensure that w_i^* lies in the feasible range for each decentralized setting as defined in Proposition 7. We start with the Production-Stackelberg game, P. First, we show that w_P^* lies in the interval $\left(\alpha_1 m, \alpha_1\left(\frac{a}{b} - \frac{ck}{\mu b}\right)\right]$.

$$\left(a - mb - 2\lambda_C^*\right)\left(\mu - \lambda_C^*\right)^2 = ck\mu > ck\left(\mu - \lambda_C^*\right)$$
$$\frac{a - 2\lambda_C^* - \frac{ck}{\mu-\lambda_C^*}}{b} > m \Rightarrow w_P^* = \alpha_1\left(\frac{a - 2\lambda_C^* - \frac{ck}{\mu-\lambda_C^*}}{b}\right) > \alpha_1 m \quad \surd$$

Note that $w_P^* = \alpha_1 m$ only when $\lambda_C^* = 0$. For $w_P^* \le \alpha_1\left(\frac{a}{b} - \frac{ck}{\mu b}\right)$, it should hold that $2\lambda_C^* \ge \frac{ck}{\mu} - \frac{ck}{\mu-\lambda_C^*}$, which reduces to $2\lambda_C^* \ge 0 \ge -\lambda_C^* \frac{ck}{\mu\left(\mu-\lambda_C^*\right)}$. According to Proposition 7, it should also hold that $w_P^* \ge w_P^{min}$. Note that it is sufficient to show $\alpha_1 m \ge w_P^{min}$, as $w_P^* \ge \alpha_1 m$. Let $g(m) = w_P^{min} - \alpha_1 m$. If we solve $g(m_0) = 0$ for m_0, we find the root to be $m_0 = -\frac{ck}{b\mu} + \frac{a}{b}$. We know from Assumption A3 that $m < -\frac{ck}{b\mu} + \frac{a}{b}$.

$$\frac{\partial g}{\partial m} = \frac{\alpha_1\left(1-\alpha_1\right)\left[\left(\alpha_1\mu - a + bm + \mu\right) + \sqrt{\left(\alpha_1\mu - a + bm + \mu\right)^2 + 4ck(1+\alpha_1)}\right]}{2\left(1+\alpha_1\right)\sqrt{\left(\alpha_1\mu - a + bm + \mu\right)^2 + 4ck(1+\alpha_1)}} \ge 0$$

As the function g is nondecreasing in m, $g(m) \le 0$ and $w_P^{min} \le \alpha_1 m$. Finally, Proposition 1 states that λ_C^* is unique as long as Assumption A3 is satisfied. Hence, w_P^* is also unique as $w_P^* = \frac{a-2\lambda_C^*-\frac{ck}{\mu-\lambda_C^*}}{b}$.

For the Marketing-Stackelberg game, M, we know that $w_M^* = \alpha_1 m \le \alpha_1\left(\frac{a}{b} - \frac{ck}{\mu b}\right)$ by Assumption A3. Since $(1-\alpha_1)p_C^* + w_M^* - m = (1-\alpha_1)p_C^* + \alpha_1 m - m = (1-\alpha_1)(p_C^* - m) \ge 0$, it also holds that $w_M^* \ge w_M^{min}$. ■

A.10 PROOF OF PROPOSITION 9

The fraction of the centralized profit that marketing achieves is less than α_1 under P, since

$$\pi_P^{MR} = (\alpha_1 p_C^* - w_P^*)\lambda_C^* < \alpha_1(p_C^* - m)\lambda_C^* = \alpha_1\pi_C^* \quad (w_P^* > \alpha_1 m)$$

while

$$\pi_M^{MR} = (\alpha_1 p_C^* - w_M^*)\lambda_C^* = \alpha_1(p_C^* - m)\lambda_C^* = \alpha_1\pi_C^* \quad (w_M^* = \alpha_1 m) \quad .■$$

A.11 ANALYSIS OF TB CONTRACT WITH NO TRANSFER PRICE

The contract parameters of the revenue-sharing contract and the transfer price-only contract satisfy the conditions described in Proposition 8. However, when $w = 0$, we demonstrate that coordination cannot be achieved. Under P, the feasible region of production's problem is the same as in the original production Stackelberg game, and hence, this contract cannot perform better. The second root of π_P^{PR} is given by $x_P^2 = \left(\frac{a}{c} - \frac{2mb}{(1-\alpha_1)c}\right) < \frac{a}{c} = x_P^1$. For $x_P^2 > 0$, the fraction of revenue offered to marketing, α_1, should not be greater than $1 - \frac{2mb}{a}$, which is positive if $a > 2mb$. Therefore, if $a \leq 2mb$, production will drive demand to zero by quoting $L_P^* = x_P^1$. In order to generate positive profits, the firm should choose α_1 such that $y_P^1 < x_P^2$, as long as $a > 2mb$. Similarly, we can easily show that under the TB contract with $w = 0$, FOC on π_M^{MR} give Equation (11). In order to generate positive profit, the firm needs to choose α_2 such that production receives positive margin, i.e., $\alpha_2 p_M^* - m \geq 0$. ■

A.12 PROOF OF PROPOSITION 10

As π_C is decreasing in μ_C, the service level constraint is tight at optimality, and $\mu_C = \lambda_C + k/L_C$. When we plug μ_C in π_C, we get $\pi_C(\lambda_C, L_C) = (a - cL_C - \lambda_C)\lambda_C/b - (m+K)\lambda_C - Kk/L_C$. First and second order conditions give:

$$\frac{\partial \pi_C(\lambda_C, L_C)}{\partial \lambda_C} = \frac{a - cL_C - 2\lambda_C}{b} - (m + K) = 0 \Rightarrow \lambda_C(L_C) = \frac{a - cL_C}{2} - \frac{(m + K)b}{2}$$

$$\frac{\partial^2 \pi_C(\lambda_C, L_C)}{\partial \lambda_C^2} = -\frac{2}{b} < 0 \Rightarrow \text{Concave}$$

Next, we plug $\lambda_C(L_C)$ in $\pi_C(\lambda_C, L_C)$, and we get

$$\pi_C(L_C) = \frac{(a - cL_C - (m + K)b)^2}{4b} - \frac{Kk}{L_C}$$

First and second order conditions give:

$$\frac{\partial \pi_C(L_C)}{\partial L_C} = \frac{c^2 L_C^3 - c(a - (m + K)b)L_C^2 + 2Kkb}{2bL_C^2} = 0 \tag{41}$$

$$\frac{\partial^2 \pi_C(L_C)}{\partial L_C^2} = \frac{c^2 L_C^3 - 4Kkb}{2bL_C^3} \tag{42}$$

Thus, the maximizer of $\pi_C(L_C)$, L_C^*, will satisfy Equation (41) as long as $L_C^* \leq L^0 = \left(\frac{4Kkb}{c^2}\right)^{\frac{1}{3}}$, where $\pi_C(L_C)$ is concave (Equation (42)). Here are some observations:

- L_C should not be greater than $(a-(m+K)b)/c$ for $\lambda_C \geq 0$.
- As $L_C \to 0$, $\frac{\partial \pi_C(L_C)}{\partial L_C} \to +\infty$, and $\left.\frac{\partial \pi_C(L_C)}{\partial L_C}\right|_{L_C=(a-(m+K)b)/c} = \left(\frac{Kkc}{a-(m+K)b}\right)^2 > 0$.
- As $L_C \to 0$, $\pi_C(L_C) \to -\infty$, and $\pi_C\left(L_C = (a-(m+K)b)/c\right) = -\frac{Kkc}{a-(m+K)b} < 0$

Thus, for Equation (41) to have a real root on $\left(0, \frac{a-(m+K)b}{c}\right]$, it should hold that $\left.\frac{\partial \pi_C(L_C)}{\partial L_C}\right|_{L_C=L^0} = -\frac{c2^{\frac{1}{3}}(a-(m+K)b)-3c^{\frac{4}{3}}(Kkb)^{\frac{1}{3}}}{4^{\frac{2}{3}}b} \leq 0$. Let $g(K)$ denote this equation as a function of K. Then,

$$g(0) = -\frac{c(a-mb)}{2b} < 0$$
$$g\left(\frac{a-mb}{b}\right) = \frac{3c^{\frac{4}{3}}((a-mb)k)^{\frac{1}{3}}}{4^{\frac{2}{3}}b} > 0$$
$$\frac{\partial g(K)}{\partial K} = \frac{c\left(2^{\frac{1}{3}}(Kbk)^{\frac{2}{3}} + c^{\frac{1}{3}}k\right)}{(4Kbk)^{\frac{2}{3}}} > 0$$

and $g(K)$ has a unique root, $\bar{K}$, on $K \in \left[0, \frac{a-mb}{b}\right]$. Thus, for all $K \leq \bar{K}$, $\pi_C(L_C)$ will be concave and its maximizer will be given by the root of Equation (41). Moreover, if $\bar{K} < K^1$, the firm will generate positive profit. For $K > \bar{K}$, $\frac{\partial \pi_C(L_C)}{\partial L_C} > 0$ for all L_C, and $\pi_C(L_C)$ is increasing, which gives $L_C^* = (a-(m+K)b)/c$. However, $\pi_C(L_C^*) < 0$, and the firm cannot generate positive profit. Similarly, for K values which make $L^0 > (a-(m+K)b)/c$, the firm can also not generate positive profit.

A change of variables gives the following set of equations at optimality for C, which is consistent with the findings of [95]:

$$\left(a - 2\lambda_C^* - (m+K)b\right)^2 \lambda_C^* = ckbK$$
$$\mu_C^* = \lambda_C^* + \sqrt{\frac{c\lambda_C^* k}{Kb}} \qquad L_C^* = \frac{k}{\mu_C^* - \lambda_C^*} \qquad p_C^* = \frac{a - cL_C^* - \lambda_C^*}{b}$$

For P, as π_P is decreasing in μ_P, the service level constraint is tight at optimality, and $\mu_P = \frac{a-cL_P}{2} + \frac{k}{L_P}$. When we plug μ_P in π_P, we get

$$\pi_P(L_P) = \frac{(a-cL_P)(a-cL_P-2(m+K)b)}{4b} - \frac{Kk}{L_P}$$

FOC give:

$$\frac{\partial \pi_P(L_P)}{\partial L_P} = \frac{c^2 L_P^3 - c(a - (m + K)b)L_P^2 + 2Kkb}{2bL_P^2} = 0$$

which is the same equation as Equation (41). Note that production will require the margin per unit that it gets to be positive, i.e., $p_P \geq (m + K)$, which gives $L_P \leq (a - (m + K)b)/c$. Moreover, K^1 and K^0 do not need to equal each other, as the objective functions values are different for different K values under the two settings.

In the decentralized setting M, the optimal capacity can be determined by FOC for the objective function with optimal lead-time and demand given as in the original decentralized setting M:

$$\frac{\partial \pi_M}{\partial \mu_M} = \frac{\partial p_M}{\partial \mu_M}\lambda_M + (p_M - m)\frac{\partial \lambda_M}{\partial \mu_M} - K = 0 \ . \blacksquare$$

APPENDIX B

ADDENDUM FOR CHAPTER 3

B.1 PROOF OF PROPOSITION 11

Optimality equations under both organizational structures, Equations (21) and (22), directly follow from the results in Chapter 2. Note that $\bar{\lambda}$ is used to ensure that $p_{i(D,\hat{J})} \geq m_i$ and is derived as follows:

$$p_{i(D,\hat{J})} = \frac{A_i - \lambda_{i(D,\hat{J})} - \frac{c_i k_i}{\mu_i - \lambda_{i(D,\hat{J})}}}{b_i} \geq m_i \quad \Rightarrow \quad (A_i - b_i m_i - \lambda_{i(D,\hat{J})})(\mu_i - \lambda_{i(D,\hat{J})}) - c_i k_i \geq 0$$

Rearranging the terms, we find the following inequality, (43), which will be satisfied if $\lambda_{i(D,\hat{J})} \leq y_1$ or $\lambda_{i(D,\hat{J})} \geq y_2$, where y_1 and y_2 are the two roots, where Equation (43) becomes zero, and y_1 is the smaller root:

$$\lambda^2_{i(D,\hat{J})} - (A_i - b_i m_i + \mu_i)\lambda_{i(D,\hat{J})} + (A_i - b_i m_i)\mu_i - c_i k_i \geq 0 \qquad (43)$$

As $y_2 > \mu_i$ while $y_1 \leq \mu_i$, it should hold that $\lambda_{i(D,\hat{J})} \leq y_1 = \bar{\lambda}$. The only requirement for the existence of the optimal solution for both organizational structures and for $\bar{\lambda} > 0$ was shown to be the assumption of $A_i - b_i m_i - c_i k_i / L_i > 0$ in Chapter 2. Note that $A_i = a_i + \beta_{ij} p_{j\cdot} + \gamma_{ij} L_{j\cdot} \geq a_i + \beta_{ij} m_j + \gamma_{ij} \frac{k_j}{\mu_j}$ as $p_{j\cdot} \geq m_j$ and $L_{j\cdot} \geq \frac{k_j}{\mu_j}$. Thus, if firm i can still generate some positive demand selling at cost and quoting the minimum possible lead-time given its service level constraint even if its competitor is selling at cost and quoting the minimum possible lead-time that satisfies its service level constraint, i.e.,

$$a_i + \beta_{ij} m_j + \gamma_{ij} \frac{k_j}{\mu_j} - b_i m_i - c_i k_i / L_i \geq 0 \qquad (44)$$

the requirement for the existence of the optimal solution is satisfied for both organizational structures. Note that condition (44) is already satisfied if each firm has a nontrivial customer base to be able to exist on its own, i.e., through Assumption A5. As shown in

Chapter 2, since the objective functions under both structures is concave, the optimal solution is unique. ■

B.2 PROOF OF PROPOSITION 12

Following a similar logic as in [113], we first show that the iterative procedure converges to a Nash Equilibrium. Let $p_{i\cdot}^{(n)}$ and $L_{i\cdot}^{(n)}$ be the solution found at the n^{th} iteration of the procedure. We will show that both $p_{i\cdot}^{(n)}$ and $L_{i\cdot}^{(n)}$ are increasing in n. As $p_{i\cdot}^{(n)}$ is bounded above (loosely) by $(a_1 + a_2)/(b_i - \beta_{ji})$ and $L_{i\cdot}^{(n)}$ is bounded above (loosely) by $(a_1 + a_2)/(c_i - \gamma_{ji})$ for $j = 3 - i,\ i = 1, 2$, this will establish that the iterative procedure converges.

From the initialization step, $p_{i\cdot}^{(0)} = m_i$ and $L_{i\cdot}^{(0)} = k_i/\mu_i$. As discussed in Assumption A5, $p_{i\cdot}^{(n)} > p_{i\cdot}^{(0)}$ and $L_{i\cdot}^{(n)} > L_{i\cdot}^{(0)}$ for all n. Let $A_i^{(n)}$ be the derived market potential for firm i at iteration n. We can begin our induction:

1. (Step $n = 1$): We know that $p_{i\cdot}^{(1)} > p_{i\cdot}^{(0)}$ and $L_{i\cdot}^{(1)} > L_{i\cdot}^{(0)}$ for $i = 1, 2$.
2. (Step $n - 1$): Assume that $p_{i\cdot}^{(n-1)} \geq p_{i\cdot}^{(n-2)}$ and $L_{i\cdot}^{(n-1)} \geq L_{i\cdot}^{(n-2)}$ for $i = 1, 2$.
3. (Step n): Given the inductive assumption from Step $n - 1$, we find

$$A_1^{(n)} = a_1 + \beta_{12} p_{2\cdot}^{(n-1)} + \gamma_{12} L_{2\cdot}^{(n-1)} \geq A_1^{(n-1)} = a_1 + \beta_{12} p_{2\cdot}^{(n-2)} + \gamma_{12} L_{2\cdot}^{(n-2)}$$

From Observation 5, we deduce that $p_{1\cdot}^{(n)} \geq p_{1\cdot}^{(n-1)}$ and $L_{1\cdot}^{(n)} \geq L_{1\cdot}^{(n-1)}$. It then follows that

$$A_2^{(n)} = a_2 + \beta_{21} p_{1\cdot}^{(n)} + \gamma_{21} L_{1\cdot}^{(n)} \geq A_2^{(n-1)} = a_2 + \beta_{21} p_{1\cdot}^{(n-1)} + \gamma_{21} L_{1\cdot}^{(n-1)}$$

Thus, $p_{2\cdot}^{(n)} \geq p_{2\cdot}^{(n-1)}$ and $L_{2\cdot}^{(n)} \geq L_{2\cdot}^{(n-1)}$, which completes our induction.

We next show the uniqueness of the subgame perfect Nash Equilibrium solution by contradiction. We can express the equilibrium solution as a function of the derived market potentials of both firms, $A_i, i = 1, 2$. Note that for any given (A_1, A_2), the optimal solution should be uniquely defined as stated in Proposition 11. Suppose that there exists two different equilibrium solutions $\Phi = (A_1, A_2)$ and $\Phi' = (A'_1, A'_2)$. By numbering the firms and the two solutions appropriately, we can assume that $A'_1 > A_1$, which results in $p'_{1\cdot} > p_{1\cdot}$ and $L'_{1\cdot} > L_{1\cdot}$ as stated in Observation 5 and we have $A'_2 > A_2$. Thus, it should hold that $\lambda'_{1\cdot} > \lambda_{1\cdot}$ and $\lambda'_{2\cdot} > \lambda_{2\cdot}$. We will show that such two solutions cannot both satisfy the optimality equations. First, we will write optimality equations only in terms of $\lambda_{1\cdot}, \lambda_{2\cdot}$. Given the best response of each firm, the generated demand at equilibrium under all organizational structures should satisfy

$$\begin{aligned}
\lambda_{1\cdot} &= a_1 + \beta_{12} p_{1\cdot} + \gamma_{12} \frac{k_2}{(\mu_2 - \lambda_{2\cdot})} - b_1 p_{1\cdot} - c_1 \frac{k_1}{(\mu_1 - \lambda_{1\cdot})} \\
\lambda_{2\cdot} &= a_2 + \beta_{21} p_{2\cdot} + \gamma_{21} \frac{k_1}{(\mu_1 - \lambda_{1\cdot})} - b_2 p_{2\cdot} - c_2 \frac{k_2}{(\mu_2 - \lambda_{2\cdot})}
\end{aligned}$$

We can extract $p_{1\cdot}$ and $p_{2\cdot}$ from these equations:

$$\begin{aligned}
p_{1\cdot} &= \frac{1}{b_1 b_2 - \beta_{12}\beta_{21}} \Bigg(b_2(a_1 - \lambda_{1\cdot}) + \frac{(\beta_{12}\gamma_{21} - b_2 c_1) k_1}{(\mu_1 - \lambda_{1\cdot})} \\
&\qquad + \beta_{12}(a_2 - \lambda_{2\cdot}) + \frac{(b_2 \gamma_{12} - c_2 \beta_{12}) k_2}{(\mu_2 - \lambda_{2\cdot})} \Bigg) \qquad (45) \\
p_{2\cdot} &= \frac{1}{b_1 b_2 - \beta_{12}\beta_{21}} \Bigg(b_1(a_2 - \lambda_{2\cdot}) + \frac{(\beta_{21}\gamma_{12} - b_1 c_2) k_2}{(\mu_2 - \lambda_{2\cdot})} \\
&\qquad + \beta_{21}(a_1 - \lambda_{1\cdot}) + \frac{(b_1 \gamma_{21} - c_1 \beta_{21}) k_1}{(\mu_1 - \lambda_{1\cdot})} \Bigg) \qquad (46)
\end{aligned}$$

First, we consider $(S^*_1, S^*_2) = (C, C)$. If we write the optimality equation of demand (Equation (21)) for both firms, we find:

$$\left(a_1 + \beta_{12} p_{2(C,C)} + \gamma_{12} \frac{k_2}{(\mu_2 - \lambda_{2(C,C)})} - 2\lambda_{1(C,C)} - m_1 b_1 \right) (\mu_1 - \lambda_{1(C,C)})^2 - c_1 k_1 \mu_1 = 0 \quad (47)$$

$$\left(a_2 + \beta_{21} p_{1(C,C)} + \gamma_{21} \frac{k_1}{(\mu_1 - \lambda_{1(C,C)})} - 2\lambda_{2(C,C)} - m_2 b_2 \right) (\mu_2 - \lambda_{2(C,C)})^2 - c_2 k_2 \mu_2 = 0 \quad (48)$$

After substituting $p_{2(C,C)}$ and $p_{1(C,C)}$ into Equations (47) and (48) from Equations (46) and

(45), respectively, and rearranging, we find the following two equations:

$$
\begin{aligned}
f^1_{CC}(\lambda_{1(C,C)}, \lambda_{2(C,C)}) \; = \; & \frac{(\beta_{21}\gamma_{12} - b_1c_2)b_2k_2\mu_2 - (b_2\gamma_{12} - c_2\beta_{12})\beta_{21}k_2\lambda_{2(C,C)}}{(\mu_2 - \lambda_{2(C,C)})^2} \\
& + \frac{(b_1\gamma_{21} - c_1\beta_{21})b_2k_1}{(\mu_1 - \lambda_{1(C,C)})} \\
& + (\beta_{12}\beta_{21} - 2b_1b_2)\lambda_{2(C,C)} - b_2\beta_{21}\lambda_{1(C,C)} + b_2\beta_{21}a_1 + b_1b_2a_2 \\
& - (b_1b_2 - \beta_{12}\beta_{21})m_2b_2 = 0 \qquad (49) \\
f^2_{CC}(\lambda_{1(C,C)}, \lambda_{2(C,C)}) \; = \; & \frac{(\beta_{12}\gamma_{21} - b_2c_1)b_1k_1\mu_1 - (b_1\gamma_{21} - c_1\beta_{21})\beta_{12}k_1\lambda_{1(C,C)}}{(\mu_1 - \lambda_{1(C,C)})^2} \\
& + \frac{(b_2\gamma_{12} - c_2\beta_{12})b_1k_2}{(\mu_2 - \lambda_{2(C,C)})} \\
& + (\beta_{12}\beta_{21} - 2b_1b_2)\lambda_{1(C,C)} - b_1\beta_{12}\lambda_{2(C,C)} + b_1\beta_{12}a_2 + b_1b_2a_1 - \\
& (b_1b_2 - \beta_{12}\beta_{21})m_1b_1 = 0 \qquad (50)
\end{aligned}
$$

For $(\lambda'_{1(C,C)}, \lambda'_{2(C,C)})$ to also be an equilibrium solution, it should hold that $f^1_{CC}(\lambda'_{1(C,C)}, \lambda'_{2(C,C)}) = f^2_{CC}(\lambda'_{1(C,C)}, \lambda'_{2(C,C)}) = 0$. It should also hold that $f^{1\Delta}_{CC} = f^1_{CC}(\lambda_{1(C,C)}, \lambda_{2(C,C)}) - f^1_{CC}(\lambda'_{1(C,C)}, \lambda'_{2(C,C)}) = 0$ and $f^{2\Delta}_{CC} = f^2_{CC}(\lambda_{1(C,C)}, \lambda_{2(C,C)}) - f^2_{CC}(\lambda'_{1(C,C)}, \lambda'_{2(C,C)}) = 0$, and therefore, $f^{\Delta}_{CC} = f^{1\Delta}_{CC} + f^{2\Delta}_{CC} = 0$. If $\lambda'_{1(C,C)} = \lambda_{1(C,C)}$ and $\lambda'_{2(C,C)} = \lambda_{2(C,C)}$, then $f^{\Delta}_{CC} = 0$. Moreover, given Assumptions A2, A3, and A4, $f^{\Delta}_{CC} > 0$ for $\lambda'_{1(C,C)} > \lambda_{1(C,C)}$ and $\lambda'_{2(C,C)} > \lambda_{2(C,C)}$. Thus, we conclude that there is a unique equilibrium solution for $(S^*_1, S^*_2) = (C, C)$. Note that even if Assumption A5 is not satisfied, if there exists a $(0 < \lambda_{1(C,C)} < \mu_1, 0 < \lambda_{2(C,C)} < \mu_2)$ pair such that a simultaneous solution to Equations (49) and (50) exists with $[(\pi_{1(C,C)} > 0, \pi_{2(C,C)} > 0)]$, then this equilibrium solution is unique. If such a solution does not exist, then, one or both of the firms may need to leave the market, and the problem turns into a monopoly. The same argument applies for the other organizational structures.

For $(S^*_1, S^*_2) = (D, D)$, Equations (47) and (48) do not have the m_1b_1 and m_2b_2 terms, respectively, but are otherwise identical. Then, $f^1_{DD}(\lambda_{1(D,D)}, \lambda_{2(D,D)}) = f^1_{CC}(\lambda_{1(C,C)}, \lambda_{2(C,C)}) + (b_1b_2 - \beta_{12}\beta_{21})m_2b_2$ and $f^2_{DD}(\lambda_{1(D,D)}, \lambda_{2(D,D)}) = f^2_{CC}(\lambda_{1(C,C)}, \lambda_{2(C,C)}) + (b_1b_2 - \beta_{12}\beta_{21})m_1b_1$, and we have $f^{\Delta}_{DD} = f^{1\Delta}_{DD} + f^{2\Delta}_{DD} = f^{\Delta}_{CC}$. Thus, uniqueness under $(S^*_1, S^*_2) = (D, D)$ directly follows from the reasoning under $(S^*_1, S^*_2) = (C, C)$. For $(S^*_1, S^*_2) = (C, D)$, Equation (48) lacks the m_2b_2 term[1]. Then, $f^1_{CD}(\lambda_{1(C,D)}, \lambda_{2(C,D)}) = f^1_{CC}(\lambda_{1(C,C)}, \lambda_{2(C,C)}) + (b_1b_2 - \beta_{12}\beta_{21})m_2b_2$ and $f^2_{CD}(\lambda_{1(C,D)}, \lambda_{2(C,D)}) = f^2_{CC}(\lambda_{1(C,C)}, \lambda_{2(C,C)})$, and we have $f^{\Delta}_{CD} = f^{1\Delta}_{CD} + f^{2\Delta}_{CD} = f^{\Delta}_{CC}$. Thus, uniqueness under $(S^*_1, S^*_2) = (C, D)$ also directly follows from the reasoning under scenario $(S^*_1, S^*_2) = (C, C)$. Note that for $(S^*_1, S^*_2) = (D, D)$ or a hybrid first stage outcome, the above results are derived assuming that the decentralized firm(s) have $\lambda^0_{i(D,\hat{J})} \geq \bar{\lambda}$. If the solution to the optimality equations is such that $\lambda^0_{i(D,\hat{J})} < \bar{\lambda}$ for firm i, then $\lambda^*_{i(D,\hat{J})} = \bar{\lambda}$ and $p^*_{i(D,\hat{J})} = m_i$. As the best response of firm $j \neq i$ to these decisions will be uniquely determined, the subgame perfect Nash Equilibrium of the game will still be unique. ■

B.3 PROOF OF PROPOSITION 13

As the firms are identical and use the same organizational structure under (C, C) and (D, D), if $(\lambda_{1\cdot}, \lambda_{2\cdot})$ is an equilibrium solution, then so must $(\lambda_{2\cdot}, \lambda_{1\cdot})$, which contradicts the uniqueness of the Nash Equilibrium. Thus, for identical firms, Equations (49) and (50) from the proof of Proposition 12 become identical. After rearranging, the optimality equations of demand under (C, C) and (D, D) become:

$$\begin{aligned} f_{CC}(\lambda^*_{(C,C)}) = \left(a - (b-\beta)m - (2 - \frac{\beta}{b})\lambda^*_{(C,C)}\right)(\mu - \lambda^*_{(C,C)})^2 - k\left((c-\gamma)\mu - (c\frac{\beta}{b} - \gamma)\lambda^*_{(C,C)}\right) &= 0 \\ f_{DD}(\lambda^*_{(D,D)}) = \left(a - (2 - \frac{\beta}{b})\lambda^*_{(D,D)}\right)(\mu - \lambda^*_{(D,D)})^2 - k\left((c-\gamma)\mu - (c\frac{\beta}{b} - \gamma)\lambda^*_{(D,D)}\right) &= 0 \end{aligned}$$

Note that as β gets closer to b, $f_{CC}(\lambda)$ approaches $f_{DD}(\lambda)$. As the difference between the decisions decreases, (D, D) may generate higher profits than (C, C) under a higher β, as discussed in the text. However, profits increase in β for both organizational structures and the difference in profits will decrease as β approaches b.

In order to compare the decisions under the two scenarios, we need to study the optimality equations more closely. We can see from $f_{CC}(\lambda)$ and $f_{DD}(\lambda)$ that $\lambda^*_{(C,C)} \neq \lambda^*_{(D,D)}$. We

[1] A similar reasoning can be applied to show uniqueness for $(S^*_1, S^*_2) = (D, C)$.

also know the following:

$$f_{CC}(0) = (a - (b - \beta)m)\mu^2 - (c - \gamma)k\mu > 0 \text{ (Assumption A5)}$$
$$f_{DD}(0) = a\mu^2 - (c - \gamma)k\mu > 0 \text{ (Assumption A5)}$$
$$f_{CC}(\mu) = f_{DD}(\mu) = (\frac{\beta}{b} - 1)ck\mu < 0$$
$$f'_{CC}(\lambda) = -(2 - \frac{\beta}{b})(\mu - \lambda)^2 - 2\left(a - (b - \beta)m - (2 - \frac{\beta}{b})\lambda\right)(\mu - \lambda) + k(c\frac{\beta}{b} - \gamma)$$
$$f'_{DD}(\lambda) = -(2 - \frac{\beta}{b})(\mu - \lambda)^2 - 2\left(a - (2 - \frac{\beta}{b})\lambda\right)(\mu - \lambda) + k(c\frac{\beta}{b} - \gamma)$$

Thus, f_{CC} starts at a lower point than f_{DD} at $\lambda = 0$, but both functions end at the same point at $\lambda = \mu$. If $c\frac{\beta}{b} - \gamma < 0$, then $f'_{DD} < 0$, $f'_{CC} < 0$ and $f'_{DD} < f'_{CC}$ at all λ. As f_{DD} decreases at a faster rate than f_{CC}, the point at which it crosses the 0 line should be larger than the one for f_{CC}, i.e., $\lambda^*_{(C,C)} < \lambda^*_{(D,D)}$. On the other hand, if $c\frac{\beta}{b} - \gamma > 0$, then $f'_{DD} < 0$, $f'_{CC} < 0$ and $f'_{DD} < f'_{CC}$ up to a certain λ for each function, which we denote by $x_{(C,C)}$ and $x_{(D,D)}$. Now, note that $f'_{CC}(x_{(C,C)}) = 0 = f'_{DD}(x_{(D,D)})$, which gives the following after rearranging:

$$\frac{\mu - x_{(C,C)}}{\mu - x_{(D,D)}} = \frac{(2 - \frac{\beta}{b})\mu + 2a - 3(2 - \frac{\beta}{b})x_{(D,D)}}{(2 - \frac{\beta}{b})\mu + 2a - 3(2 - \frac{\beta}{b})x_{(C,C)} - 2(b - \beta)m}$$

If $x_{(C,C)} \geq x_{(D,D)}$, the left hand side of this equation becomes ≤ 1, while the right hand side becomes greater than 1. Thus, we should have $x_{(C,C)} < x_{(D,D)}$, which indicates that f_{CC} starts to increase at an earlier point than f_{DD}. Between $\lambda = x_{(C,C)}$ and $\lambda = x_{(D,D)}$, we have $f'_{CC} > 0$ and $f'_{DD} < 0$, while beyond $\lambda = x_{(D,D)}$, both f'_{CC} and f'_{DD} are positive. Note that we have $f'_{DD} < f'_{CC}$. Thus, also under this case, the point at which f_{DD} crosses the 0 line should be larger than the one for f_{CC}, i.e., $\lambda^*_{(C,C)} < \lambda^*_{(D,D)}$. As the optimal lead-time and price are given by $L_{\cdot} = \frac{k}{\mu - \lambda_{\cdot}}$ and $p_{\cdot} = \frac{a - \lambda_{\cdot} - (c - \gamma)L_{\cdot}}{b - \beta}$, respectively, it follows that $L^*_{(C,C)} < L^*_{(D,D)}$ and $p^*_{(C,C)} > p^*_{(D,D)}$. For the comparison of profits, after rearranging, we see that:

$$\pi^*_{(C,C)} - \pi^*_{(D,D)} = \frac{\lambda^*_{(C,C)} - \lambda^*_{(D,D)}}{b - \beta}\left[\left(a - (\lambda^*_{(C,C)} + \lambda^*_{(D,D)}) - m(b - \beta)\right) - \frac{(c - \gamma)k\mu}{(\mu - \lambda^*_{(C,C)})(\mu - \lambda^*_{(D,D)})}\right]$$

Replacing $(c - \gamma)k\mu$ with $\left(a - (b - \beta)m - (2 - \frac{\beta}{b})\lambda^*_{(C,C)}\right)(\mu - \lambda^*_{(C,C)})^2 + k(c\frac{\beta}{b} - \gamma)\lambda^*_{(C,C)}$ from

$f_{(C,C)}(\lambda^*_{(C,C)}) = 0$, we find:

$$\pi^*_{(C,C)} - \pi^*_{(D,D)} = \frac{\lambda^*_{(C,C)} - \lambda^*_{(D,D)}}{b-\beta}\left[\left(a - (\lambda^*_{(C,C)} + \lambda^*_{(D,D)}) - m(b-\beta)\right) - \frac{\left(a - (b-\beta)m - (2-\frac{\beta}{b})\lambda^*_{(C,C)}\right)(\mu - \lambda^*_{(C,C)})}{(\mu - \lambda^*_{(D,D)})}\right] + \frac{\lambda^*_{(C,C)} - \lambda^*_{(D,D)}}{b-\beta}\left[-\frac{k(c\frac{\beta}{b} - \gamma)\lambda^*_{(C,C)}}{(\mu - \lambda^*_{(C,C)})(\mu - \lambda^*_{(D,D)})}\right]$$

As $\lambda^*_{(C,C)} - \lambda^*_{(D,D)} < 0, \mu - \lambda^*_{(C,C)} > \mu - \lambda^*_{(D,D)}$ and $\lambda^*_{(C,C)}(1-\frac{\beta}{b}) < \lambda^*_{(D,D)}$, the first term of this equation is positive. If $c\frac{\beta}{b} - \gamma \geq 0$, then the second term is non-negative, and $\pi^*_{(C,C)} - \pi^*_{(D,D)} > 0$. Otherwise, $\pi^*_{(D,D)}$ may be higher than $\pi^*_{(C,C)}$. Note that the condition $\frac{\beta}{b} \geq \frac{\gamma}{c}$ will be explored and interpreted in detail in Proposition 14.

For scenario (C, D), given that $f^1_{CD}(\lambda_{1(C,D)}, \lambda_{2(C,D)})$ and $f^2_{CD}(\lambda_{1(C,D)}, \lambda_{2(C,D)})$ are defined as in the proof of Proposition 12, we find:

$$\begin{aligned} &f^1_{CD}(\lambda_{1(C,D)}, \lambda_{2(C,D)}) - f^2_{CD}(\lambda_{1(C,D)}, \lambda_{2(C,D)}) \\ &= \frac{(\gamma\beta - cb)bk\mu - (b\gamma - c\beta)\beta k\lambda_{2(C,D)}}{(\mu - \lambda_{2(C,D)})^2} - \frac{(\gamma\beta - cb)bk\mu - (b\gamma - c\beta)\beta k\lambda_{1(C,D)}}{(\mu - \lambda_{1(C,D)})^2} \\ &+ \frac{(b\gamma - c\beta)bk}{\mu - \lambda_{1(C,D)}} - \frac{(b\gamma - c\beta)bk}{\mu - \lambda_{2(C,D)}} \\ &+ (\beta^2 - 2b^2)(\lambda_{2(C,D)} - \lambda_{1(C,D)}) + b\beta(\lambda_{2(C,D)} - \lambda_{1(C,D)}) + (b^2 - \beta^2)mb \end{aligned}$$

which can equal zero only when $\lambda_{2(C,D)} > \lambda_{1(C,D)}$. Then, it follows that $L_{2(C,D)} > L_{1(C,D)}$ as $L_{\cdot} = \frac{k}{\mu - \lambda_{\cdot}}$. Using Equations (45) and (46), we can see that $p_{2(C,D)} < p_{1(C,D)}$ as $\mu > \lambda_{2(C,D)}$ and $\mu > \lambda_{1(C,D)}$:

$$p_{1(C,D)} - p_{2(C,D)} = \frac{(\lambda_{2(C,D)} - \lambda_{1(C,D)})\left[(\mu - \lambda_{2(C,D)})(\mu - \lambda_{1(C,D)}) + (c+\gamma)k\right]}{(\beta + b)(\mu - \lambda_{2(C,D)})(\mu - \lambda_{1(C,D)})}$$

However, either firm may generate higher profits as shown in the example in Table 2. ■

B.4 PROOF OF PROPOSITIONS 14 and 15

We prove the non-identical firms setting, as the identical firms setting is a special case of the former. Consider the equilibrium solution under (C, C), $(\{p^*_{1(C,C)}, L^*_{1(C,C)}\}, \{p^*_{2(C,C)}, L^*_{2(C,C)}\})$.

Without loss of generality, assume that firm 2 decides to switch to a decentralized organizational structure. Thus, we use the equilibrium solution under (C, C) as the starting point of the iterative procedure for the game under (C, D). In response to $\{p^*_{1(C,C)}, L^*_{1(C,C)}\}$, Firm 2 will quote a lower price and a higher lead-time than $\{p^*_{2(C,C)}, L^*_{2(C,C)}\}$ with a decentralized structure leading to an increase in demand but decrease in profits. Let us denote the new decisions by $(\{p^{(1)}_{2(C,D)}, L^{(1)}_{2(C,D)}\}$. If the net effect of this change is a decrease in the derived market potential for Firm 1, the iterative procedure will proceed in a monotonically decreasing fashion for the decisions and profits until the equilibrium is reached, and both firms will end up worse under (C, D) than under (C, C). However, if the net change is an increase, then, Firm 1 will end up generating higher profits, while Firm 2 may or may not generate generate higher profits under (C, D) than under (C, C). Thus, a centralized organizational structure may or may not be dominant for Firm 2 when the competitor employs a centralized structure.

We are interested in the negative net effect case on Firm 1 for the centralized structure to be guaranteed to be dominant for Firm 2. Then, it should hold that

$$
\begin{aligned}
A_1^{(1)} = a_1 + \beta_{12} p^{(1)}_{2(C,D)} + \gamma_{12} L^{(1)}_{2(C,D)} \quad &< \quad A_1^* = a_1 + \beta_{12} p^*_{2(C,C)} + \gamma_{12} L^*_{2(C,C)} \\
\Rightarrow \quad \gamma_{12}(L^{(1)}_{2(C,D)} - L^*_{2(C,C)}) \quad &< \quad \beta_{12}(p^*_{2(C,C)} - p^{(1)}_{2(C,C)}) \\
&= \beta_{12}\left(\frac{A_2^* - \lambda^*_{2(C,C)} - c_2 L^*_{2(C,C)} - (A_2^* - \lambda^{(1)}_{2(C,D)} - c_2 L^{(1)}_{2(C,D)})}{b_2}\right) \\
&= \beta_{12}\left(\frac{(\lambda^{(1)}_{2(C,D)} - \lambda^*_{2(C,C)}) + c_2(L^{(1)}_{2(C,D)} - L^*_{2(C,C)})}{b_2}\right)
\end{aligned}
$$

As $\lambda^{(1)}_{2(C,D)} > \lambda^*_{2(C,C)}$ and $L^{(1)}_{2(C,D)} > L^*_{2(C,C)}$, it holds that $\frac{(\lambda^{(1)}_{2(C,D)} - \lambda^*_{2(C,C)}) + c_2(L^{(1)}_{2(C,D)} - L^*_{2(C,C)})}{b_2} > \frac{c_2(L^{(1)}_{2(C,D)} - L^*_{2(C,C)})}{b_2}$. Thus, if $\gamma_{12}(L^{(1)}_{2(C,D)} - L^*_{2(C,C)}) \leq \beta_{12}\left(\frac{c_2(L^{(1)}_{2(C,D)} - L^*_{2(C,C)})}{b_2}\right)$, which reduces to $\frac{\gamma_{12}}{c_2} \leq \frac{\beta_{12}}{b_2}$, then, $A_1^{(1)} < A_1^*$ and $(C, C)_{12} \succ (C, D)_{12}$. The same condition applies when we compare (D, C) vs. (D, D), and we see that $(D, C)_{12} \succ (D, D)_{12}$. Thus, if $\frac{\gamma_{12}}{c_2} \leq \frac{\beta_{12}}{b_2}$, a centralized organizational structure is dominant for Firm 2. A similar logic can be used to compare (C, C) vs. (D, C) and (C, D) vs. (D, D) to find that if $\frac{\gamma_{21}}{c_1} \leq \frac{\beta_{21}}{b_1}$, $(C, C)_{12} \succ (D, C)_{12}$ and $(C, D)_{12} \succ (D, D)_{12}$, and a centralized organizational structure is dominant for Firm 1. ■

B.5 DERIVATIONS FOR SECTION 3.6.1

The equilibrium price for each organizational structure (with $j \neq i, j \in \{1,2\}$) is given as follows:

$$\begin{aligned}
p^*_{i(C,C)} &= \frac{1}{4b_1b_2 - \beta_{12}\beta_{21}}\Big(\beta_{ij}(a_j + \gamma_{ji}L_i - c_jL_j + b_jm_j) + 2b_j(a_i + \gamma_{ij}L_j - c_iL_i + b_im_i)\Big)\\
p^*_{i(D,D)} &= p^*_{i(C,C)} - \frac{1}{4b_1b_2 - \beta_{12}\beta_{21}}\Big(\beta_{ij}b_jm_j + 2b_ib_jm_i\Big)\\
p^*_{1(C,D)} &= p^*_{1(C,C)} - \frac{1}{4b_1b_2 - \beta_{12}\beta_{21}}(\beta_{12}b_2m_2)\,; \quad p^*_{2(C,D)} = p^*_{2(C,C)} - \frac{1}{4b_1b_2 - \beta_{12}\beta_{21}}(2b_1b_2m_2)\\
p^*_{1(D,C)} &= p^*_{1(C,C)} - \frac{1}{4b_1b_2 - \beta_{12}\beta_{21}}(2b_1b_2m_1)\,; \quad p^*_{2(D,C)} = p^*_{2(C,C)} - \frac{1}{4b_1b_2 - \beta_{12}\beta_{21}}(\beta_{21}b_1m_1)
\end{aligned}$$

We assume that $\Big(\beta_{ij}(a_j + \gamma_{ji}L_i - c_jL_j) + 2b_j(a_i + \gamma_{ij}L_j - c_iL_i)\Big) > 0$ for $p^*_{i(D,D)} > 0$. It can be shown that $p^*_{i(C,C)} > m_i$ $(i = 1,2)$, $p^*_{1(C,D)} > m_1$ and $p^*_{2(D,C)} > m_2$ by Assumption A5. We assume for the rest of the analysis that the parameters of the problem are such that $p^*_{1(D,C)}$, $p^*_{2(C,D)}$ and $p^*_{i(D,D)}$ $(i = 1,2)$ are at least the unit production cost. Otherwise, the firm will be selling at cost. It can be observed that $p^*_{i\cdot}$ decreases in L_j if $(c_j\beta_{ij} - 2b_j\gamma_{ij}) > 0$ or equivalently, $\frac{\beta_{ij}}{b_j} > 2\frac{\gamma_{ij}}{c_j}$, while it decreases in L_i. One can also observe that $p^*_{i(C,C)} > \left[p^*_{i(C,D)}, p^*_{i(D,C)}\right] > p^*_{i(D,D)}$. For $p^*_{1(C,D)} > p^*_{1(D,C)}$, we should have $p^*_{1(C,D)} - p^*_{1(D,C)} = \frac{1}{4b_1b_2 - \beta_{12}}(2b_1b_2m_1 - \beta_{12}b_2m_2) > 0$, or equivalently, $\frac{m_1}{m_2} > \frac{\beta_{12}}{2b_1}$.

Given the optimal prices, the optimal demand under each organizational structure will be:

$$\begin{aligned}
\lambda^*_{i(C,C)} &= b_i(p^*_{i(C,C)} - m_i),\ \lambda^*_{i(D,D)} = b_ip^*_{i(C,C)},\ i = 1,2\\
\lambda^*_{1(C,D)} &= b_1(p^*_{1(C,D)} - m_1);\ \ \lambda^*_{1(D,C)} = b_1p^*_{1(C,D)};\ \ \lambda^*_{2(D,C)} = b_2(p^*_{2(D,C)} - m_2);\ \ \lambda^*_{2(C,D)} = b_2p^*_{2(C,D)}
\end{aligned}$$

Let $x, y \in \{(C,C),(C,D),(D,C),(D,D)\}$. Then, $\lambda^*_{ix} - \lambda^*_{iy} = b_i(p^*_{iy} - p^*_{ix}) + \beta_{ij}(p^*_{jx} - p^*_{jy})$ for $i, j \in \{1,2\},\ j \neq i$. In other words,

$$\lambda^*_{ix} - \lambda^*_{iy} > 0 \quad \text{if} \quad \frac{p^*_{iy} - p^*_{ix}}{p^*_{jy} - p^*_{jx}} > \frac{\beta_{ij}}{b_i}$$

Thus, we find the following for Firm 1 (similar results can be developed for Firm 2):

$$
\begin{aligned}
\lambda^*_{1(D,D)} - \lambda^*_{1(C,D)} &> 0 \quad \text{since} \quad \frac{p^*_{1(C,D)} - p^*_{1(D,D)}}{p^*_{2(C,D)} - p^*_{2(D,D)}} = \frac{2b_1b_2m_1}{\beta_{21}b_1m_1} > \frac{\beta_{12}}{b_1} \\
\lambda^*_{1(D,D)} - \lambda^*_{1(D,C)} &< 0 \quad \text{since} \quad \frac{p^*_{1(D,C)} - p^*_{1(D,D)}}{p^*_{2(D,C)} - p^*_{2(D,D)}} = \frac{\beta_{12}b_2m_2}{2b_1b_2m_2} < \frac{\beta_{12}}{b_1} \\
\lambda^*_{1(D,C)} - \lambda^*_{1(C,C)} &> 0 \quad \text{since} \quad \frac{p^*_{1(C,C)} - p^*_{1(D,C)}}{p^*_{2(C,C)} - p^*_{2(D,C)}} = \frac{2b_1b_2m_1}{\beta_{21}b_1m_1} > \frac{\beta_{12}}{b_1} \\
\lambda^*_{1(D,D)} - \lambda^*_{1(C,C)} &> 0 \quad \text{if} \quad \frac{p^*_{1(C,C)} - p^*_{1(D,D)}}{p^*_{2(C,C)} - p^*_{2(D,D)}} = \frac{2b_1b_2m_1 + \beta_{12}b_2m_2}{2b_1b_2m_2 + \beta_{21}b_1m_1} > \frac{\beta_{12}}{b_1} \Rightarrow \frac{m_1}{m_2} > \frac{\beta_{12}b_2}{2b_1b_2 - \beta_1\beta_2} = A_1
\end{aligned}
$$

In order to compare profits, we need to check $\pi^*_{ix} - \pi^*_{iy} = p^*_{ix}\lambda^*_{ix} - p^*_{iy}\lambda^*_{iy} - m_i(\lambda^*_{ix} - \lambda^*_{iy})$. From Table 4, we can immediately see that $\pi^*_{1(C,C)} > \pi^*_{1(C,D)}$, $\pi^*_{2(C,C)} > \pi^*_{2(D,C)}$, $\pi^*_{1(D,C)} > \pi^*_{1(D,D)}$, $\pi^*_{2(C,D)} > \pi^*_{2(D,D)}$. Moreover,

$$
\begin{aligned}
\pi^*_{1(C,D)} - \pi^*_{1(D,D)} &= \frac{b_1m_1}{(4b_1b_2 - \beta_{12}\beta_{21})^2}\Big[(2b_1b_2 - \beta_{12}\beta_{21})^2 m_1 \\
&\qquad + \beta_{12}\beta_{21}\left(2b_2(a_1 - c_1L_1 + \gamma_{12}L_2) + \beta_{12}(a_2 - c_2L_2 + \gamma_{21}L_1)\right)\Big] > 0 \\
\pi^*_{1(C,C)} - \pi^*_{1(D,C)} &= \frac{b_1m_1}{(4b_1b_2 - \beta_{12}\beta_{21})^2}\Big[(2b_1b_2 - \beta_{12}\beta_{21})^2 m_1 \\
&\qquad + \beta_{12}\beta_{21}\left(2b_2(a_1 - c_1L_1 + \gamma_{12}L_2) + \beta_{12}(a_2 - c_2L_2 + \gamma_{21}L_1 + b_2m_2)\right)\Big] > 0 \\
\pi^*_{2(C,C)} - \pi^*_{2(C,D)} &= \frac{b_2m_2}{(4b_1b_2 - \beta_{12}\beta_{21})^2}\Big[(2b_1b_2 - \beta_{12}\beta_{21})^2 m_2 \\
&\qquad + \beta_{12}\beta_{21}\left(2b_1(a_2 - c_2L_2 + \gamma_{21}L_1) + \beta_{21}(a_1 - c_1L_1 + \gamma_{12}L_2 + b_1m_1)\right)\Big] > 0 \\
\pi^*_{2(D,C)} - \pi^*_{2(D,D)} &= \frac{b_2m_2}{(4b_1b_2 - \beta_{12}\beta_{21})^2}\Big[(2b_1b_2 - \beta_{12}\beta_{21})^2 m_2 \\
&\qquad + \beta_{12}\beta_{21}\left(2b_1(a_2 - c_2L_2 + \gamma_{21}L_1) + \beta_{21}(a_1 - c_1L_1 + \gamma_{12}L_2)\right)\Big] > 0
\end{aligned}
$$

Thus, we find that $\pi^*_{i(C,C)} > \left[\pi^*_{i(C,D)}, \pi^*_{i(D,C)}\right] > \pi^*_{i(D,D)}$. Table 12 provides identification of the optimal prices, generated demand and profits under different first stage outcomes for identical firms. ■

B.6 DERIVATIONS FOR SECTION 3.6.2

For the case of identical firms, define $A = a - (b - \beta)p$. The best response function of each firm is given by:

$$f(L_i) = cL_i^2 - (A + \gamma L_j - \mu)L_i - k \geq 0, \quad (i, j) \in \{1, 2\}, \ i \neq j \tag{51}$$

Table 12: Unconstrained Price Competition for Identical Firms

(C,C)	**(C,D)-(D,C)**	**(D,D)**
$p_{1(C,C)} = p_{2(C,C)}$ $p_{2(C,C)} = \frac{a+bm-(c-\gamma)L}{2b-\beta}$	$p_{1(C,D)} = p_{2(D,C)} = p_{1(C,C)} - \frac{\beta bm}{4b^2-\beta^2}$ $p_{1(D,C)} = p_{2(C,D)} = p_{1(C,C)} - \frac{2b^2m}{4b^2-\beta^2}$	$p_{1(D,D)} = p_{2(D,D)}$ $p_{2(D,D)} = p_{2(C,C)} - \frac{bm}{2b-\beta}$
$\lambda_{1(C,C)} = \lambda_{2(C,C)}$ $\lambda_{2(C,C)} = b(p_{2(C,C)} - m)$	$\lambda_{1(C,D)} = \lambda_{2(D,C)} = b(p_{1(C,D)} - m)$ $\lambda_{1(D,C)} = \lambda_{2(C,D)} = b(p_{1(D,C)})$	$\lambda_{1(D,D)} = \lambda_{2(D,D)}$ $\lambda_{2(D,D)} = b(p_{2(D,D)})$
$\pi_{1(C,C)} = \pi_{2(C,C)}$ $\pi_{2(C,C)} = \frac{\lambda^2_{2(C,C)}}{b}$	$\pi_{1(C,D)} = \pi_{2(D,C)} = \frac{\lambda^2_{1(C,D)}}{b}$ $\pi_{1(D,C)} = \pi_{2(C,D)} = \frac{\lambda^2_{1(D,C)}}{b} - m\lambda_{1(D,C)}$	$\pi_{1(D,D)} = \pi_{2(D,D)}$ $\pi_{2(D,D)} = \frac{\lambda^2_{2(D,D)}}{b} - m\lambda_{2(D,D)}$

Suppose that $L_1 = L_2$. Then, Equation (51) becomes:

$$f(L) = (c-\gamma)L^2 - (A-\mu)L - k \geq 0$$

The optimal solution is given by the positive root of $f(L)$:

$$L^* = \frac{a-(b-\beta)p-\mu + \sqrt{(a-(b-\beta)p-\mu)^2 + 4(c-\gamma)k}}{2(c-\gamma)}$$

Conversely, suppose that $L_1 \neq L_2$. Then, Equation (51) for $i = 1, 2$ gives $L_1 + L_2 = \frac{A-\mu}{c}$. Substituting $L_2 = \frac{A-\mu}{c} - L_1$ into Equation (51) for $i = 1$, we find that $L_1^* = \frac{A-\mu+\sqrt{(A-\mu)^2+4ck/(c+\gamma)}}{2c} > 0$ and $L_2^* = \frac{A-\mu-\sqrt{(A-\mu)^2+4ck/(c+\gamma)}}{2c} < 0$, which is not a valid equilibrium. Thus, $L_1^* = L_2^* = L^*$.

It can be observed that L^* decreases in p and increases in β. We next consider $\frac{\partial L}{\partial \gamma}$:

$$\frac{\partial L}{\partial \gamma} = \frac{a-(b-\beta)p-\mu + \sqrt{(a-(b-\beta)p-\mu)^2 + 4(c-\gamma)k}}{2(c-\gamma)^2} - \frac{4k}{4(c-\gamma)\sqrt{(a-(b-\beta)p-\mu)^2 + 4(c-\gamma)k}}$$

We find that $\frac{\partial L}{\partial \gamma} > 0$ since:

- If $a-(b-\beta)p-\mu \geq 0$:

$$\frac{\sqrt{(a-(b-\beta)p-\mu)^2 + 4(c-\gamma)k}}{2(c-\gamma)^2} >^? \frac{4k}{4(c-\gamma)\sqrt{(a-(b-\beta)p-\mu)^2 + 4(c-\gamma)k}}$$
$$\Rightarrow (a-(b-\beta)p-\mu)^2 + 4(c-\gamma)k > 2(c-\gamma)k \ \checkmark$$

- If $a-(b-\beta)p-\mu<0$:

$$
\begin{aligned}
&\frac{a-(b-\beta)p-\mu+\sqrt{(a-(b-\beta)p-\mu)^2+4(c-\gamma)k}}{2(c-\gamma)^2}\\
&\qquad >^? \frac{4k}{4(c-\gamma)\sqrt{(a-(b-\beta)p-\mu)^2+4(c-\gamma)k}}\\
&\Rightarrow (a-(b-\beta)p-\mu)\sqrt{(a-(b-\beta)p-\mu)^2+4(c-\gamma)k}\\
&\qquad +(a-(b-\beta)p-\mu)^2+2(c-\gamma)k >^? 0\\
&\Rightarrow (a-(b-\beta)p-\mu)^2+2(c-\gamma)k\\
&\qquad >^? (\mu-a+(b-\beta)p)\sqrt{(a-(b-\beta)p-\mu)^2+4(c-\gamma)k}\\
&\Rightarrow (a-(b-\beta)p-\mu)^4+4(c-\gamma)k(a-(b-\beta)p-\mu)^2+4(c-\gamma)^2k^2\\
&\qquad >^? (a-(b-\beta)p-\mu)^4+4(c-\gamma)k(a-(b-\beta)p-\mu)^2\\
&\Rightarrow 4(c-\gamma)^2k^2>0\ \surd
\end{aligned}
$$

Therefore, L^* increases in γ. ■

APPENDIX C

ADDENDUM FOR CHAPTER 4

C.1 *FITTING MIXTURE OF GAUSSIAN DISTRIBUTIONS FOR CLUSTERING DEPARTURE TIME*

Mixture of Gaussian functions is obtained as a weighted sum of individual Gaussian functions. Thus, the probability distribution of a mixture of k Gaussian functions in n dimensions would look like:

$$p(\mathbf{x}, \mathbf{w}) = \sum_{k=1}^{K} w_k p(\mathbf{x}; \mu_\mathbf{k}, \mathbf{\Sigma_k})$$

where

$$p(\mathbf{x}; \mu_\mathbf{k}, \mathbf{\Sigma_k}) = \frac{1}{(\sqrt{2\pi})^n \sqrt{|\mathbf{\Sigma_k}|}} e^{-\frac{1}{2}(\mathbf{x}-\mu_\mathbf{k})^T \Sigma^{-1} (\mathbf{x}-\mu_\mathbf{k})}$$

and

$$w_k \geq 0, \ \forall k = 1...N; \quad \sum_{k=1}^{K} w_k = 1$$

One of the most common methods to learn the parameters of a Gaussian mixture is the expectation-maximization (EM) method [34]. The EM method is an efficient iterative procedure that computes the Maximum Likelihood (ML) estimate of the unknown model parameter(s) for which the observed data are generated most likely from. Each iteration of the EM algorithm consists of two steps. In the expectation step, E-step, the missing data are estimated given the observed data and current estimate of the model parameters through conditional likelihood computation. In the maximization step, M-step, the likelihood function is maximized under the assumption that the missing data are known using the estimate of the missing data from the E-step. The method tries to maximize the difference between the likelihood values computed at each iteration, and the likelihood value increases at each iteration. For computational details, the reader is referred to [34, 122, 19]. We tested three publicly available codes from the MATLAB Central File Exchange website, and used the result that was agreed by all [124, 125, 50].

Tables 13 and 14 show the parameters of the multi-modal Gaussian distribution fit of departure time for PoS='A' and PoS='D', respectively. Three time slots are created for PoS='A' and two time slots are created for PoS='D'. The valleys of the multi-modal distribution represent where the end points of each time slot are defined. For example, "**1-2**" represents where the first time slot ends and the second time slot starts. For this analysis, we measure the departure time in number of minutes using 5:00 AM as our reference point, i.e., $t = 0$. In the "VALLEYS" column, we give the value in minutes as well as the translation back to the actual time of day.

Table 13: Multi-modal Gaussian Distribution of Time Slots for PoS = 'A'

				$TimeSlot$			**VALLEYS**	
PoS	$Cmpt$	Dow	**Parameters**	**1**	**2**	**3**	**1-2**	**2-3**
'A'	'Frst'	'Sun'	Mean	205.22	442.79	765.32	283 /	592 /
			Std. dev.	30.68	105.42	94.91	9:43	14:52
			Weight	0.15	0.38	0.46		
'A'	'Frst'	'Mon'	Mean	151.07	741.55	424.62	315 /	567 /
			Std. dev.	68.65	87.10	134.99	10:15	14:27
			Weight	0.36	0.31	0.33		
'A'	'Frst'	'Tue'	Mean	150.48	424.29	744.61	316 /	570 /
			Std. dev.	68.09	144.30	85.06	10:16	14:30
			Weight	0.35	0.35	0.30		
'A'	'Frst'	'Wed'	Mean	150.71	448.04	758.73	317 /	584 /
			Std. dev.	69.00	152.98	80.64	10:17	14:44
			Weight	0.34	0.37	0.29		
'A'	'Frst'	'Thu'	Mean	152.01	461.75	771.76	314 /	607 /
			Std. dev.	69.02	159.34	79.16	10:14	15:07
			Weight	0.32	0.42	0.26		
'A'	'Frst'	'Fri'	Mean	190.52	572.46	816.01	381 /	690 /
			Std. dev.	97.53	136.74	53.30	11:21	16:30
			Weight	0.36	0.39	0.24		
'A'	'Frst'	'Sat'	Mean	162.36	386.93	783.10	288 /	674 /
			Std. dev.	52.92	129.65	52.20	9:48	16:14
			Weight	0.37	0.55	0.07		
'A'	'Econ'	'Sun'	Mean	205.09	413.69	745.81	281 /	598 /
			Std. dev.	30.65	92.70	107.79	9:41	14:58
			Weight	0.22	0.46	0.32		
'A'	'Econ'	'Mon'	Mean	145.65	405.60	728.75	316 /	580 /
			Std. dev.	74.57	144.43	101.41	10:16	14:40
			Weight	0.34	0.42	0.24		
'A'	'Econ'	'Tue'	Mean	149.54	468.63	778.96	324 /	662 /
			Std. dev.	78.44	164.83	79.75	10:24	16:02
			Weight	0.36	0.50	0.14		
'A'	'Econ'	'Wed'	Mean	153.75	483.32	799.62	326 /	675 /
			Std. dev.	79.07	167.32	68.88	10:26	16:15
			Weight	0.34	0.51	0.15		
'A'	'Econ'	'Thu'	Mean	154.03	526.42	816.55	327 /	688 /
			Std. dev.	83.08	167.31	59.00	10:27	16:28
			Weight	0.31	0.50	0.19		
'A'	'Econ'	'Fri'	Mean	130.30	508.67	814.05	290 /	675 /
			Std. dev.	77.39	171.55	56.59	9:50	16:15
			Weight	0.23	0.50	0.27		
'A'	'Econ'	'Sat'	Mean	158.64	414.08	789.40	276 /	677 /
			Std. dev.	49.55	133.37	50.10	9:36	16:17
			Weight	0.32	0.56	0.12		

Table 14: Multi-modal Gaussian Distribution of Time Slots for PoS = 'D'

				$TimeSlot$		**VALLEYS**
PoS	$Cmpt$	Dow	**Parameters**	**1**	**2**	**1-2**
'D'	'Frst'	'Sun'	Mean	517.33	788.94	549 /
			Std. dev.	161.02	84.79	14:09
			Weight	0.33	0.67	
'D'	'Frst'	'Mon'	Mean	374.15	768.45	532 /
			Std. dev.	197.98	80.33	13:52
			Weight	0.29	0.71	
'D'	'Frst'	'Tue'	Mean	381.03	760.83	515 /
			Std. dev.	195.45	79.35	13:35
			Weight	0.22	0.78	
'D'	'Frst'	'Wed'	Mean	361.52	758.17	512 /
			Std. dev.	186.65	80.25	13:32
			Weight	0.20	0.80	
'D'	'Frst'	'Thu'	Mean	341.95	757.44	510 /
			Std. dev.	182.72	81.66	13:30
			Weight	0.20	0.80	
'D'	'Frst'	'Fri'	Mean	344.25	737.88	472 /
			Std. dev.	179.14	90.98	12:52
			Weight	0.22	0.78	
'D'	'Frst'	'Sat'	Mean	439.49	803.82	663 /
			Std. dev.	171.90	49.40	16:03
			Weight	0.52	0.48	
'D'	'Econ'	'Sun'	Mean	522.05	817.82	631 /
			Std. dev.	168.70	73.73	15:31
			Weight	0.50	0.50	
'D'	'Econ'	'Mon'	Mean	338.11	776.16	537 /
			Std. dev.	213.53	92.42	13:57
			Weight	0.45	0.55	
'D'	'Econ'	'Tue'	Mean	414.73	778.26	526 /
			Std. dev.	223.26	91.22	13:46
			Weight	0.45	0.55	
'D'	'Econ'	'Wed'	Mean	440.42	774.10	498 /
			Std. dev.	213.51	91.36	13:18
			Weight	0.40	0.60	
'D'	'Econ'	'Thu'	Mean	415.16	772.45	501 /
			Std. dev.	217.25	91.55	13:21
			Weight	0.36	0.64	
'D'	'Econ'	'Fri'	Mean	455.97	783.33	518 /
			Std. dev.	226.97	86.10	13:38
			Weight	0.41	0.59	
'D'	'Econ'	'Sat'	Mean	479.73	808.28	674 /
			Std. dev.	179.04	46.75	16:14
			Weight	0.54	0.46	

C.2 BASIC STATISTICS FOR GROSS TICKET FARE

We display the number of observations, N, mean, standard deviation, coefficient of variation, CV (std.dev. / mean), the minimum and maximum values of the gross ticket fare amounts by PoS, $MktSegType$ and $SatStay$ in Table 15 (before aggregation is performed at the classification group level). It can be observed that the average prices paid were significantly different in economy and first class compartments. The difference can also be observed if there was a Saturday night stay, particularly for late purchases.

Table 15: Basic Statistics for Gross Ticket Fare

PoS	$MktSegType$	Sat_Stay	N	Mean	Std. Dev.	CV	Min	Max
'A'	'EconAdvn'	0	64236	38.25	19.01	49.70%	14.50	149
'A'	'EconAdvn'	1	109038	40.91	13.80	33.74%	14.50	149
'A'	'EconLate'	0	163865	79.73	42.65	53.50%	14.50	149
'A'	'EconLate'	1	154000	54.29	19.55	36.00%	14.50	149
'A'	'FrstAdvn'	0	16764	91.24	57.57	63.09%	25.00	280
'A'	'FrstAdvn'	1	19921	74.66	28.78	38.55%	39.46	280
'A'	'FrstLate'	0	89810	170.62	58.69	34.40%	25.00	280
'A'	'FrstLate'	1	32766	109.15	52.44	48.04%	25.00	280
'D'	'EconAdvn'	0	28976	38.47	25.42	66.09%	10.00	149
'D'	'EconAdvn'	1	101135	32.87	13.70	41.69%	10.00	158
'D'	'EconLate'	0	68058	82.68	44.62	53.97%	15.00	399
'D'	'EconLate'	1	102965	43.08	18.05	41.91%	10.00	230
'D'	'FrstAdvn'	0	5422	164.46	51.61	31.38%	25.00	280
'D'	'FrstAdvn'	1	6387	89.03	43.43	48.79%	25.00	347
'D'	'FrstLate'	0	55605	180.33	34.43	19.09%	42.59	280
'D'	'FrstLate'	1	13463	104.91	53.91	51.39%	25.00	280

C.3 PEARSON CORRELATION COEFFICIENTS FOR MODEL 1

In this section, we provide the significant Pearson correlation coefficients for *ln_Pax* for *PoS* ='A' and *PoS* ='D' in Figures 16 and 17, respectively, and for *ln_Pratio* in Figure 18, which are greater/less than $+/-0.20$.

Table 16: Pearson Correlation Coefficients for *ln_Pax* in Model 1 (*PoS*=‘A’)

PoS	*MktSegType*	*Sat_Stay*	*Time_Slot*	*ln_lag_Pax*	*ln_PRatio*	*Rdd_Index*	*Sun*	*Mon*	*Tue*	*Wed*	*Thu*	*Fri*	*Sat*
‘A’	‘EconAdvn’	0	1	0.55				0.26	0.20			-0.26	-0.29
‘A’	‘EconAdvn’	0	2	0.55								-0.28	-0.34
‘A’	‘EconAdvn’	0	3	0.39				0.25					-0.22
‘A’	‘EconAdvn’	1	1	0.85			-0.33	-0.25	-0.35	-0.23		0.48	0.47
‘A’	‘EconAdvn’	1	2	0.85			-0.35	-0.39	-0.31		0.27	0.51	0.31
‘A’	‘EconAdvn’	1	3	0.80					-0.33	-0.23	0.29	0.65	
‘A’	‘EconLate’	0	1	0.41	0.33	-0.28		0.23					-0.32
‘A’	‘EconLate’	0	2	0.42	0.40	-0.46							-0.21
‘A’	‘EconLate’	0	3	0.44	0.41	-0.52		0.24					-0.21
‘A’	‘EconLate’	1	1	0.69			-0.41		-0.26			0.43	0.45
‘A’	‘EconLate’	1	2	0.76			-0.35	-0.39	-0.26		0.20	0.48	0.39
‘A’	‘EconLate’	1	3	0.68					-0.28	-0.21	0.21	0.60	
‘A’	‘FrstAdvn’	0	1				-0.27						
‘A’	‘FrstAdvn’	0	2	0.43				0.30				-0.23	-0.30
‘A’	‘FrstAdvn’	0	3	0.21								-0.22	
‘A’	‘FrstAdvn’	1	1	0.69				-0.27	-0.27	-0.29	-0.20	0.58	
‘A’	‘FrstAdvn’	1	2	0.70			-0.29	-0.28	-0.28	-0.31		0.49	0.23
‘A’	‘FrstAdvn’	1	3	0.75			-0.28	-0.23	-0.23	-0.23		0.66	
‘A’	‘FrstLate’	0	1	0.40		-0.38	-0.29						
‘A’	‘FrstLate’	0	2	0.36	0.27	-0.45							
‘A’	‘FrstLate’	0	3	0.47	0.24	-0.42						-0.24	-0.24
‘A’	‘FrstLate’	1	1	0.50				-0.22	-0.23	-0.26		0.40	0.34
‘A’	‘FrstLate’	1	2	0.61			-0.27	-0.24	-0.25	-0.22		0.42	0.38
‘A’	‘FrstLate’	1	3	0.58	0.23	-0.20		-0.23	-0.22		0.21	0.51	

Table 17: Pearson Correlation Coefficients for *ln_Pax* in Model 1 (*PoS* = 'D')

PoS	*MktSegType*	*Sat_ Stay*	*Time_ Slot*	*ln_lag_ Pax*	*ln_ PRatio*	*Rdd_ Index*	*Sun*	*Mon*	*Tue*	*Wed*	*Thu*	*Fri*	*Sat*
'D'	'EconAdvn'	0	1	0.51									0.53
'D'	'EconAdvn'	0	2	0.68			-0.47	-0.28			0.26		0.23
'D'	'EconAdvn'	1	1	0.79		0.23	0.47	0.31		-0.32	-0.35	-0.29	
'D'	'EconAdvn'	1	2	0.83	-0.27		0.49	0.25					-0.51
'D'	'EconLate'	0	1	0.26	0.22		-0.23						0.24
'D'	'EconLate'	0	2	0.43	0.32	-0.24	-0.44				0.20		
'D'	'EconLate'	1	1	0.76		0.21	0.51	0.34		-0.25	-0.28	-0.31	
'D'	'EconLate'	1	2	0.78	-0.39	0.37	0.51	0.22					-0.37
'D'	'FrstAdvn'	0	1										
'D'	'FrstAdvn'	0	2	0.31			-0.22					0.22	-0.29
'D'	'FrstAdvn'	1	1	0.27			0.30						
'D'	'FrstAdvn'	1	2	0.51			0.52						
'D'	'FrstLate'	0	1	0.35		-0.24	-0.23						
'D'	'FrstLate'	0	2	0.48		-0.24	-0.34						-0.31
'D'	'FrstLate'	1	1	0.34			0.36						
'D'	'FrstLate'	1	2	0.60	0.28		0.67			-0.21	-0.20	-0.20	

Table 18: Pearson Correlation Coefficients for *ln_Pratio* in Model 1

PoS	*MktSegType*	*Sat_Stay*	*Time_Slot*	*ln_lag_Pax*	*ln_lag_PRatio*	*Rdd_Index*	*Sun*	*Sat*
‘A’	‘EconAdvn’	0	1		0.36	-0.39		
‘A’	‘EconAdvn’	0	2		0.28	-0.31		
‘A’	‘EconAdvn’	0	3			-0.24		
‘A’	‘EconAdvn’	1	1		0.21	-0.30		
‘A’	‘EconAdvn’	1	2		0.43	-0.44		
‘A’	‘EconAdvn’	1	3		0.25	-0.27		
‘A’	‘EconLate’	0	1	0.21	0.52	-0.59		
‘A’	‘EconLate’	0	2	0.22	0.50	-0.62		
‘A’	‘EconLate’	0	3	0.21	0.42	-0.50		
‘A’	‘EconLate’	1	1		0.37	-0.47		
‘A’	‘EconLate’	1	2		0.60	-0.61		
‘A’	‘EconLate’	1	3		0.57	-0.58		
‘A’	‘FrstAdvn’	0	1					
‘A’	‘FrstAdvn’	0	2					
‘A’	‘FrstAdvn’	0	3					
‘A’	‘FrstAdvn’	1	1					
‘A’	‘FrstAdvn’	1	2					
‘A’	‘FrstAdvn’	1	3					
‘A’	‘FrstLate’	0	1		0.33	-0.36		
‘A’	‘FrstLate’	0	2		0.25	-0.36		
‘A’	‘FrstLate’	0	3			-0.27		
‘A’	‘FrstLate’	1	1		0.35	-0.51		
‘A’	‘FrstLate’	1	2		0.25	-0.42		
‘A’	‘FrstLate’	1	3		0.32	-0.48		
‘D’	‘EconAdvn’	0	1			-0.32		
‘D’	‘EconAdvn’	0	2		0.27	-0.35		
‘D’	‘EconAdvn’	1	1		0.31	-0.36		
‘D’	‘EconAdvn’	1	2		0.41	-0.36		
‘D’	‘EconLate’	0	1		0.32	-0.39		
‘D’	‘EconLate’	0	2		0.54	-0.46		
‘D’	‘EconLate’	1	1		0.37	-0.54		
‘D’	‘EconLate’	1	2	-0.38	0.71	-0.63		
‘D’	‘FrstAdvn’	0	1		-0.46			
‘D’	‘FrstAdvn’	0	2					0.24
‘D’	‘FrstAdvn’	1	1					
‘D’	‘FrstAdvn’	1	2					
‘D’	‘FrstLate’	0	1					
‘D’	‘FrstLate’	0	2		0.27			
‘D’	‘FrstLate’	1	1				0.21	
‘D’	‘FrstLate’	1	2		0.21	-0.24	0.25	

C.4 OLS and 2SLS Results for Outbound Trips, Economy Class Advance Purchases

In the following figures, for each classification group based on $SatStay$ and $TimeSlot$ under PoS='A', $MktSegType$ ='EconAdvn', we first provide the results from the stepwise OLS estimation followed by the results from the 2SLS estimation.

The REG Procedure
Model: MODEL1
Dependent Variable: LN_PAX

Number of Observations Read	1469
Number of Observations Used	1469

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	14	1823.87859	130.27704	375.16	<.0001
Error	1454	504.90560	0.34725		
Corrected Total	1468	2328.78419			

Root MSE	0.58928	R-Square	0.7832
Dependent Mean	2.08717	Adj R-Sq	0.7811
Coeff Var	28.23346		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	1.37340	0.07447	18.44	<.0001	0
LN_PRATIO	1	-0.40710	0.09001	-4.52	<.0001	1.03445
LN_LAG_PAX	1	0.41786	0.02258	18.50	<.0001	3.69800
PUBHOL	1	-0.61376	0.11511	-5.33	<.0001	1.12138
SUN	1	-0.99363	0.07509	-13.23	<.0001	1.91052
MON	1	-0.66820	0.06335	-10.55	<.0001	1.92062
TUE	1	-0.87439	0.06601	-13.25	<.0001	2.09459
WED	1	-0.56334	0.05966	-9.44	<.0001	1.94593
FRI	1	0.55094	0.06101	9.03	<.0001	2.07904
SAT	1	0.51044	0.06032	8.46	<.0001	2.06838
JAN	1	-0.22964	0.05755	-3.99	<.0001	1.07502
FEB	1	-0.18233	0.05768	-3.16	0.0016	1.05592
MAY	1	-0.18873	0.05977	-3.16	0.0016	1.09042
SEP	1	-0.09551	0.05417	-1.76	0.0781	1.04964
LN_AVGCONN	1	0.22427	0.05670	3.96	<.0001	1.08796

Figure 19: Stepwise OLS Estimation Results for PoS='A', $MktSegType$='EconAdvn', $SatStay$=1, $TimeSlot = 1$

Two-Stage Least Squares Estimation

Model	LN_PAX
Dependent Variable	LN_PAX

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	14	1833.924	130.9946	312.34	<.0001
Error	1454	609.8037	0.419397		
Corrected Total	1468	2328.784			

Root MSE	0.64761	R-Square	0.75046
Dependent Mean	2.08717	Adj R-Sq	0.74806
Coeff Var	31.02802		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	1.572459	0.089881	17.49	<.0001
LN_PRATIO	1	-1.97150	0.308314	-6.39	<.0001
LN_LAG_PAX	1	0.396246	0.025145	15.76	<.0001
PUBHOL	1	-0.66474	0.126863	-5.24	<.0001
SUN	1	-1.09372	0.084607	-12.93	<.0001
MON	1	-0.70444	0.069952	-10.07	<.0001
TUE	1	-0.93834	0.073524	-12.76	<.0001
WED	1	-0.55123	0.065605	-8.40	<.0001
FRI	1	0.527993	0.067180	7.86	<.0001
SAT	1	0.457119	0.067033	6.82	<.0001
JAN	1	-0.19035	0.063673	-2.99	0.0028
FEB	1	-0.17343	0.063415	-2.73	0.0063
MAY	1	-0.24126	0.066412	-3.63	0.0003
SEP	1	-0.06893	0.059736	-1.15	0.2487
LN_AVGCONN	1	0.173024	0.063047	2.74	0.0061

Figure 20: 2SLS Estimation Results for PoS='A', $MktSegType$='EconAdvn', $SatStay$=1, $TimeSlot = 1$

The REG Procedure
Model: MODEL1
Dependent Variable: LN_PAX

Number of Observations Read	1642
Number of Observations Used	1642

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	15	1801.72347	120.11490	426.24	<.0001
Error	1626	458.20971	0.28180		
Corrected Total	1641	2259.93317			

Root MSE	0.53085	R-Square	0.7972
Dependent Mean	2.57010	Adj R-Sq	0.7954
Coeff Var	20.65482		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	1.26436	0.08192	15.43	<.0001	0
LN_PRATIO	1	-0.62968	0.09306	-6.77	<.0001	1.03989
LN_LAG_PAX	1	0.45662	0.02108	21.66	<.0001	3.66426
SUN	1	-0.47719	0.04989	-9.56	<.0001	1.77257
MON	1	-0.67225	0.05259	-12.78	<.0001	1.73137
TUE	1	-0.42592	0.04979	-8.55	<.0001	1.72703
THU	1	0.47935	0.05137	9.33	<.0001	1.90562
FRI	1	0.82363	0.06050	13.61	<.0001	2.56899
SAT	1	0.57958	0.05279	10.98	<.0001	1.99141
JAN	1	-0.32121	0.04932	-6.51	<.0001	1.19070
FEB	1	-0.11623	0.05020	-2.32	0.0207	1.11541
MAY	1	-0.22934	0.05136	-4.47	<.0001	1.25265
JUN	1	-0.12727	0.04814	-2.64	0.0083	1.12075
SEP	1	-0.13548	0.04825	-2.81	0.0050	1.11231
NOV	1	-0.08320	0.04842	-1.72	0.0859	1.11332
LN_AVGCONN	1	0.28258	0.07431	3.80	0.0001	1.07599

Figure 21: Stepwise OLS Estimation Results for PoS=‘A’, $MktSegType$=‘EconAdvn’, $SatStay$=1, $TimeSlot = 2$

Two-Stage Least Squares Estimation

Model	LN_PAX
Dependent Variable	LN_PAX

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	16	1823.043	113.9402	357.16	<.0001
Error	1625	518.4081	0.319020		
Corrected Total	1641	2259.933			

Root MSE	0.56482	R-Square	0.77860
Dependent Mean	2.57010	Adj R-Sq	0.77642
Coeff Var	21.97651		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	1.448440	0.090477	16.01	<.0001
LN_PRATIO	1	-2.00257	0.194333	-10.30	<.0001
LN_LAG_PAX	1	0.442309	0.022522	19.64	<.0001
PUBHOL	1	-0.18758	0.099807	-1.88	0.0604
SUN	1	-0.52915	0.054838	-9.65	<.0001
MON	1	-0.73311	0.057651	-12.72	<.0001
TUE	1	-0.44589	0.054516	-8.18	<.0001
THU	1	0.460479	0.056536	8.14	<.0001
FRI	1	0.717524	0.067041	10.70	<.0001
SAT	1	0.547359	0.058097	9.42	<.0001
JAN	1	-0.33390	0.052511	-6.36	<.0001
FEB	1	-0.15210	0.053621	-2.84	0.0046
MAY	1	-0.25046	0.054803	-4.57	<.0001
JUN	1	-0.11779	0.051315	-2.30	0.0218
SEP	1	-0.13024	0.051422	-2.53	0.0114
NOV	1	-0.09847	0.051593	-1.91	0.0565
LN_AVGCONN	1	0.265522	0.079096	3.36	0.0008

Figure 22: 2SLS Estimation Results for PoS='A', $MktSegType$='EconAdvn', $SatStay$=1, $TimeSlot = 2$

The REG Procedure
Model: MODEL1
Dependent Variable: LN_PAX

Number of Observations Read	1568
Number of Observations Used	1568

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	11	1533.01409	139.36492	366.30	<.0001
Error	1556	592.00922	0.38047		
Corrected Total	1567	2125.02332			

Root MSE	0.61682	R-Square	0.7214
Dependent Mean	2.01780	Adj R-Sq	0.7194
Coeff Var	30.56894		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	1.00609	0.06226	16.16	<.0001	0
LN_PRATIO	1	-0.19961	0.08823	-2.26	0.0238	1.04725
LN_LAG_PAX	1	0.41728	0.02108	19.79	<.0001	2.66669
MON	1	-0.19760	0.05905	-3.35	0.0008	1.60595
TUE	1	-0.43052	0.06239	-6.90	<.0001	1.79285
WED	1	-0.21336	0.05851	-3.65	0.0003	1.72737
THU	1	0.64769	0.05818	11.13	<.0001	1.78993
FRI	1	1.12009	0.06845	16.36	<.0001	2.41701
SAT	1	-0.30375	0.06031	-5.04	<.0001	1.73180
JAN	1	-0.27269	0.05526	-4.93	<.0001	1.02327
SEP	1	-0.21409	0.05525	-3.87	0.0001	1.02301
LN_AVGCONN	1	0.34533	0.06072	5.69	<.0001	1.22522

Figure 23: Stepwise OLS Estimation Results for PoS=‘A’, $MktSegType$=‘EconAdvn’, $SatStay$=1, $TimeSlot = 3$

Two-Stage Least Squares Estimation

Model LN_PAX
Dependent Variable LN_PAX

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	11	1551.504	141.0458	290.86	<.0001
Error	1556	754.5550	0.484932		
Corrected Total	1567	2125.023			

Root MSE	0.69637	R-Square	0.67279
Dependent Mean	2.01780	Adj R-Sq	0.67048
Coeff Var	34.51132		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	1.102635	0.072005	15.31	<.0001
LN_PRATIO	1	-2.02323	0.311655	-6.49	<.0001
LN_LAG_PAX	1	0.409489	0.023832	17.18	<.0001
MON	1	-0.20275	0.066670	-3.04	0.0024
TUE	1	-0.39902	0.070622	-5.65	<.0001
WED	1	-0.13303	0.067320	-1.98	0.0483
THU	1	0.714949	0.066582	10.74	<.0001
FRI	1	1.024183	0.078824	12.99	<.0001
SAT	1	-0.41327	0.070361	-5.87	<.0001
JAN	1	-0.29813	0.062521	-4.77	<.0001
SEP	1	-0.17289	0.062733	-2.76	0.0059
LN_AVGCONN	1	0.440669	0.070268	6.27	<.0001

Figure 24: 2SLS Estimation Results for PoS=‘A’, $MktSegType$=‘EconAdvn’, $SatStay$=1, $TimeSlot = 3$

```
                          The REG Procedure
                            Model: MODEL1
                     Dependent Variable: LN_PAX

               Number of Observations Read        1603
               Number of Observations Used        1603
```

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	13	328.40405	25.26185	98.22	<.0001
Error	1589	408.67313	0.25719		
Corrected Total	1602	737.07718			

Root MSE	0.50714	R-Square	0.4455
Dependent Mean	2.59598	Adj R-Sq	0.4410
Coeff Var	19.53547		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	1.49414	0.07096	21.06	<.0001	0
LN_PRATIO	1	-0.40341	0.06939	-5.81	<.0001	1.03644
LN_LAG_PAX	1	0.35514	0.02167	16.39	<.0001	1.43654
PUBHOL	1	0.31590	0.09410	3.36	0.0008	1.17880
MON	1	0.38900	0.05174	7.52	<.0001	1.89965
TUE	1	0.35803	0.04925	7.27	<.0001	1.88440
WED	1	0.27323	0.04857	5.63	<.0001	1.84591
THU	1	0.20511	0.04926	4.16	<.0001	1.89893
FRI	1	-0.22689	0.05163	-4.39	<.0001	1.92982
SAT	1	-0.33440	0.05225	-6.40	<.0001	1.99937
JAN	1	-0.25704	0.04579	-5.61	<.0001	1.08208
FEB	1	-0.12763	0.04648	-2.75	0.0061	1.05228
MAY	1	-0.21483	0.05056	-4.25	<.0001	1.12857
LN_AVGCONN	1	0.28736	0.06221	4.62	<.0001	1.22579

Figure 25: Stepwise OLS Estimation Results for PoS='A', $MktSegType$='EconAdvn', $SatStay$=0, $TimeSlot = 1$

Two-Stage Least Squares Estimation

Model	LN_PAX
Dependent Variable	LN_PAX

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	13	333.1026	25.62328	93.60	<.0001
Error	1589	435.0146	0.273766		
Corrected Total	1602	737.0772			

Root MSE	0.52323	R-Square	0.43366
Dependent Mean	2.59598	Adj R-Sq	0.42903
Coeff Var	20.15523		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	1.581937	0.075303	21.01	<.0001
LN_PRATIO	1	-1.10562	0.158076	-6.99	<.0001
LN_LAG_PAX	1	0.357870	0.022364	16.00	<.0001
PUBHOL	1	0.359566	0.097484	3.69	0.0002
MON	1	0.431848	0.054072	7.99	<.0001
TUE	1	0.394947	0.051346	7.69	<.0001
WED	1	0.312633	0.050730	6.16	<.0001
THU	1	0.264852	0.052220	5.07	<.0001
FRI	1	-0.20354	0.053478	-3.81	0.0001
SAT	1	-0.26701	0.055579	-4.80	<.0001
JAN	1	-0.28891	0.047679	-6.06	<.0001
FEB	1	-0.16241	0.048456	-3.35	0.0008
MAY	1	-0.22030	0.052172	-4.22	<.0001
LN_AVGCONN	1	0.232066	0.065134	3.56	0.0004

Figure 26: 2SLS Estimation Results for PoS='A', $MktSegType$='EconAdvn', $SatStay$=0, $TimeSlot = 1$

The REG Procedure
Model: MODEL1
Dependent Variable: LN_PAX

Number of Observations Read	1648
Number of Observations Used	1648

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	10	456.26228	45.62623	118.03	<.0001
Error	1637	632.79487	0.38656		
Corrected Total	1647	1089.05715			

Root MSE	0.62174	R-Square	0.4190
Dependent Mean	2.22838	Adj R-Sq	0.4154
Coeff Var	27.90094		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	2.09673	0.08161	25.69	<.0001	0
LN_PRATIO	1	-0.29956	0.07218	-4.15	<.0001	1.02729
LN_LAG_PAX	1	0.27856	0.02316	12.03	<.0001	1.61626
TUE	1	0.11503	0.04685	2.46	0.0142	1.14398
THU	1	-0.18980	0.04786	-3.97	<.0001	1.20644
FRI	1	-0.62861	0.05272	-11.92	<.0001	1.40193
SAT	1	-0.72416	0.05326	-13.60	<.0001	1.40968
JAN	1	-0.44381	0.05611	-7.91	<.0001	1.11054
MAY	1	-0.46429	0.05797	-8.01	<.0001	1.14244
NOV	1	-0.12567	0.05470	-2.30	0.0217	1.04254
LN_AVGCONN	1	-0.32786	0.07506	-4.37	<.0001	1.02321

Figure 27: Stepwise OLS Estimation Results for PoS =‘A’, $MktSegType$=‘EconAdvn’, $SatStay$=0, $TimeSlot = 2$

Two-Stage Least Squares Estimation

Model	LN_PAX
Dependent Variable	LN_PAX

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	10	477.6275	47.76275	98.95	<.0001
Error	1637	790.1587	0.482687		
Corrected Total	1647	1089.057			

Root MSE	0.69476	R-Square	0.37674
Dependent Mean	2.22838	Adj R-Sq	0.37293
Coeff Var	31.17773		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	2.324598	0.097252	23.90	<.0001
LN_PRATIO	1	-1.75581	0.230433	-7.62	<.0001
LN_LAG_PAX	1	0.244191	0.026373	9.26	<.0001
TUE	1	0.155302	0.052689	2.95	0.0032
THU	1	-0.16713	0.053582	-3.12	0.0018
FRI	1	-0.71742	0.060360	-11.89	<.0001
SAT	1	-0.84025	0.061954	-13.56	<.0001
JAN	1	-0.45131	0.062711	-7.20	<.0001
MAY	1	-0.48831	0.064875	-7.53	<.0001
NOV	1	-0.16232	0.061361	-2.65	0.0082
LN_AVGCONN	1	-0.25602	0.084544	-3.03	0.0025

Figure 28: 2SLS Estimation Results for PoS=‘A’, $MktSegType$=‘EconAdvn’, $SatStay$=0, $TimeSlot = 2$

```
                                  The REG Procedure
                                    Model: MODEL1
                              Dependent Variable: LN_PAX

                        Number of Observations Read        1357
                        Number of Observations Used        1357


                                Analysis of Variance

                                          Sum of           Mean
      Source                   DF        Squares         Square    F Value    Pr > F

      Model                    12      153.44037       12.78670      31.56    <.0001
      Error                  1344      544.53381        0.40516
      Corrected Total        1356      697.97417


                   Root MSE              0.63652    R-Square     0.2198
                   Dependent Mean        1.15933    Adj R-Sq     0.2129
                   Coeff Var            54.90435


                                Parameter Estimates

                                Parameter       Standard                                Variance
   Variable            DF        Estimate          Error    t Value    Pr > |t|        Inflation

   Intercept            1         0.85414        0.04369      19.55      <.0001                0
   LN_PRATIO            1         0.06139        0.05830       1.05      0.2925          1.02443
   LN_LAG_PAX           1         0.28826        0.02493      11.56      <.0001          1.15046
   PUBHOL               1         0.24306        0.10996       2.21      0.0272          1.04591
   MON                  1         0.32642        0.05144       6.35      <.0001          1.09502
   SAT                  1        -0.32647        0.06166      -5.29      <.0001          1.09555
   JAN                  1        -0.26811        0.06522      -4.11      <.0001          1.09647
   MAY                  1        -0.12646        0.07314      -1.73      0.0841          1.08662
   JUL                  1        -0.18749        0.05997      -3.13      0.0018          1.10731
   SEP                  1        -0.14741        0.06382      -2.31      0.0211          1.09970
   OCT                  1        -0.11934        0.06355      -1.88      0.0606          1.09045
   NOV                  1        -0.17293        0.06123      -2.82      0.0048          1.11023
   LN_AVGCONN           1         0.14261        0.05193       2.75      0.0061          1.03809
```

Figure 29: Stepwise OLS Estimation Results for PoS =‘A’, $MktSegType$=‘EconAdvn’, $SatStay$=0, $TimeSlot$ = 3

Two-Stage Least Squares Estimation

Model	LN_PAX
Dependent Variable	LN_PAX

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	12	153.1844	12.76536	31.16	<.0001
Error	1344	550.5969	0.409670		
Corrected Total	1356	697.9742			

Root MSE	0.64005	R-Square	0.21766
Dependent Mean	1.15933	Adj R-Sq	0.21067
Coeff Var	55.20917		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	0.881065	0.051917	16.97	<.0001
LN_PRATIO	1	-0.16414	0.238992	-0.69	0.4923
LN_LAG_PAX	1	0.288602	0.025075	11.51	<.0001
PUBHOL	1	0.225962	0.111960	2.02	0.0438
MON	1	0.332094	0.052049	6.38	<.0001
SAT	1	-0.35010	0.066587	-5.26	<.0001
JAN	1	-0.26207	0.065880	-3.98	<.0001
MAY	1	-0.12096	0.073765	-1.64	0.1013
JUL	1	-0.20125	0.061933	-3.25	0.0012
SEP	1	-0.13412	0.065612	-2.04	0.0411
OCT	1	-0.11993	0.063908	-1.88	0.0608
NOV	1	-0.17816	0.061808	-2.88	0.0040
LN_AVGCONN	1	0.142386	0.052220	2.73	0.0065

Figure 30: 2SLS Estimation Results for PoS='A', $MktSegType$='EconAdvn', $SatStay$=0, $TimeSlot = 3$

C.5 OLS and 2SLS Results for Outbound Trips, Economy Class Late Purchases

In the following figures, for each classification group based on $SatStay$ and $TimeSlot$ under PoS='A', $MktSegType$ ='EconLate', we first provide the results from the stepwise OLS estimation followed by the results from the 2SLS estimation.

The REG Procedure
Model: MODEL1
Dependent Variable: LN_PAX

Number of Observations Read	3932
Number of Observations Used	3932

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	16	3170.70279	198.16892	536.00	<.0001
Error	3915	1447.43634	0.36972		
Corrected Total	3931	4618.13914			

Root MSE	0.60804	R-Square	0.6866
Dependent Mean	1.79193	Adj R-Sq	0.6853
Coeff Var	33.93217		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	1.10762	0.04169	26.57	<.0001	0
LN_PRATIO	1	0.05558	0.05018	1.11	0.2681	1.36727
LN_LAG_PAX	1	0.24537	0.01591	15.43	<.0001	3.22309
PUBHOL	1	-0.23111	0.07427	-3.11	0.0019	1.06905
RDDINDEX	1	-0.01573	0.00328	-4.80	<.0001	1.58161
RDD5	1	-0.53248	0.03697	-14.40	<.0001	1.05570
RDD9	1	-0.17384	0.03723	-4.67	<.0001	1.06397
RDD0	1	-1.04715	0.04360	-24.02	<.0001	1.35894
SUN	1	-0.61623	0.03862	-15.96	<.0001	1.43311
TUE	1	-0.16584	0.03241	-5.12	<.0001	1.30269
THU	1	0.56458	0.03324	16.99	<.0001	1.55639
FRI	1	1.14670	0.04098	27.98	<.0001	2.30024
SAT	1	1.22047	0.04105	29.73	<.0001	2.34938
JAN	1	-0.12689	0.03465	-3.66	0.0003	1.03799
FEB	1	-0.07627	0.03556	-2.14	0.0320	1.02518
NOV	1	-0.06011	0.03505	-1.72	0.0864	1.02646
LN_AVGCONN	1	0.20925	0.03696	5.66	<.0001	1.13371

Figure 31: Stepwise OLS Estimation Results for PoS='A', $MktSegType$='EconLate', $SatStay$=1, $TimeSlot = 1$

Two-Stage Least Squares Estimation

Model	LN_PAX
Dependent Variable	LN_PAX

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	17	3173.347	186.6674	478.94	<.0001
Error	3914	1525.472	0.389747		
Corrected Total	3931	4618.139			

Root MSE	0.62430	R-Square	0.67535
Dependent Mean	1.79193	Adj R-Sq	0.67394
Coeff Var	34.83930		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	1.297018	0.077063	16.83	<.0001
LN_PRATIO	1	-0.67382	0.258101	-2.61	0.0091
LN_LAG_PAX	1	0.244534	0.016343	14.96	<.0001
PUBHOL	1	-0.24938	0.076820	-3.25	0.0012
RDDINDEX	1	-0.03417	0.007230	-4.73	<.0001
RDD5	1	-0.52149	0.038138	-13.67	<.0001
RDD9	1	-0.18278	0.038356	-4.77	<.0001
RDD0	1	-0.97237	0.051658	-18.82	<.0001
SUN	1	-0.64932	0.041331	-15.71	<.0001
TUE	1	-0.14943	0.033768	-4.43	<.0001
THU	1	0.555010	0.034312	16.18	<.0001
FRI	1	1.148878	0.042096	27.29	<.0001
SAT	1	1.178500	0.044912	26.24	<.0001
JAN	1	-0.11814	0.036176	-3.27	0.0011
FEB	1	-0.06243	0.037330	-1.67	0.0945
MAY	1	-0.01603	0.036296	-0.44	0.6588
NOV	1	-0.05618	0.036363	-1.54	0.1225
LN_AVGCONN	1	0.118904	0.049309	2.41	0.0159

Figure 32: 2SLS Estimation Results for PoS='A', $MktSegType$='EconLate', $SatStay$=1, $TimeSlot = 1$

The REG Procedure
Model: MODEL1
Dependent Variable: LN_PAX

Number of Observations Read 4236
Number of Observations Used 4236

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	18	3596.56367	199.80909	602.23	<.0001
Error	4217	1399.12101	0.33178		
Corrected Total	4235	4995.68468			

Root MSE	0.57600	R-Square	0.7199
Dependent Mean	2.22466	Adj R-Sq	0.7187
Coeff Var	25.89176		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	1.58265	0.05199	30.44	<.0001	0
LN_PRATIO	1	0.06200	0.05806	1.07	0.2857	1.65073
LN_LAG_PAX	1	0.27013	0.01475	18.32	<.0001	3.38502
PUBHOL	1	-0.41526	0.06348	-6.54	<.0001	1.16266
RDDINDEX	1	-0.00729	0.00307	-2.38	0.0175	1.68389
RDD5	1	-0.55179	0.03405	-16.21	<.0001	1.03656
RDD9	1	-0.12109	0.03392	-3.57	0.0004	1.06414
SUN	1	-0.60444	0.03523	-17.16	<.0001	1.92071
MON	1	-0.75153	0.03833	-19.61	<.0001	1.93934
TUE	1	-0.41830	0.03460	-12.09	<.0001	1.83543
THU	1	0.48112	0.03441	13.98	<.0001	1.89649
FRI	1	1.02743	0.03998	25.70	<.0001	2.47365
SAT	1	0.84712	0.03757	22.55	<.0001	2.22490
JAN	1	-0.14194	0.03212	-4.42	<.0001	1.07826
FEB	1	-0.11939	0.03291	-3.63	0.0003	1.06205
SEP	1	0.08747	0.03175	2.75	0.0059	1.06625
OCT	1	0.09730	0.03146	3.09	0.0020	1.07345
DEC	1	-0.07085	0.03199	-2.21	0.0268	1.06943
LN_AVGCONN	1	0.08697	0.04657	1.87	0.0619	1.10622

Figure 33: Stepwise OLS Estimation Results for PoS=‘A’, $MktSegType$=‘EconLate’, $SatStay$=1, $TimeSlot = 2$

Two-Stage Least Squares Estimation

Model	LN_PAX
Dependent Variable	LN_PAX

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	18	3597.886	199.8826	590.07	<.0001
Error	4217	1428.482	0.338744		
Corrected Total	4235	4995.685			

Root MSE	0.58202	R-Square	0.71580
Dependent Mean	2.22466	Adj R-Sq	0.71459
Coeff Var	26.16203		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	1.770579	0.058616	30.21	<.0001
LN_PRATIO	1	-0.47234	0.163241	-2.89	0.0038
LN_LAG_PAX	1	0.272784	0.014928	18.27	<.0001
PUBHOL	1	-0.43063	0.064313	-6.70	<.0001
RDDINDEX	1	-0.02441	0.005786	-4.22	<.0001
RDD5	1	-0.54616	0.034425	-15.87	<.0001
RDD9	1	-0.11613	0.034308	-3.38	0.0007
SUN	1	-0.61630	0.035793	-17.22	<.0001
MON	1	-0.78412	0.040032	-19.59	<.0001
TUE	1	-0.42525	0.034973	-12.16	<.0001
THU	1	0.451299	0.035607	12.67	<.0001
FRI	1	0.975548	0.042336	23.04	<.0001
SAT	1	0.809474	0.039720	20.38	<.0001
JAN	1	-0.11919	0.033585	-3.55	0.0004
FEB	1	-0.12252	0.033697	-3.64	0.0003
SEP	1	0.089011	0.032528	2.74	0.0062
OCT	1	0.107916	0.032311	3.34	0.0008
NOV	1	0.005097	0.033160	0.15	0.8779
DEC	1	-0.06439	0.032843	-1.96	0.0500

Figure 34: 2SLS Estimation Results for PoS =‘A’, $MktSegType$=‘EconLate’, $SatStay$=1, $TimeSlot = 2$

The REG Procedure
Model: MODEL1
Dependent Variable: LN_PAX

Number of Observations Read	4154
Number of Observations Used	4154

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	16	2583.24063	161.45254	377.86	<.0001
Error	4137	1767.66829	0.42728		
Corrected Total	4153	4350.90892			

Root MSE	0.65367	R-Square	0.5937
Dependent Mean	1.93963	Adj R-Sq	0.5922
Coeff Var	33.70065		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	1.26997	0.04494	28.26	<.0001	0
LN_PRATIO	1	0.05233	0.05485	0.95	0.3401	1.54170
LN_LAG_PAX	1	0.35746	0.01486	24.05	<.0001	2.28772
RDDINDEX	1	-0.02876	0.00334	-8.62	<.0001	1.51822
RDD5	1	-0.54575	0.03882	-14.06	<.0001	1.03276
MON	1	-0.10914	0.03808	-2.87	0.0042	1.56420
TUE	1	-0.24422	0.03886	-6.28	<.0001	1.67098
WED	1	-0.11442	0.03750	-3.05	0.0023	1.62091
THU	1	0.52625	0.03846	13.68	<.0001	1.80672
FRI	1	1.14110	0.04523	25.23	<.0001	2.45092
SAT	1	0.20317	0.03685	5.51	<.0001	1.62473
JAN	1	-0.21335	0.03737	-5.71	<.0001	1.08267
FEB	1	-0.11553	0.03762	-3.07	0.0021	1.05881
MAY	1	-0.07127	0.03606	-1.98	0.0482	1.06793
JUL	1	0.07842	0.03569	2.20	0.0281	1.06795
DEC	1	-0.19860	0.03712	-5.35	<.0001	1.07914
LN_AVGCONN	1	0.14042	0.03865	3.63	0.0003	1.12475

Figure 35: Stepwise OLS Estimation Results for PoS=‘A’, $MktSegType$=‘EconLate’, $SatStay$=1, $TimeSlot = 3$

Two-Stage Least Squares Estimation

Model	LN_PAX
Dependent Variable	LN_PAX

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	17	2592.415	152.4950	340.92	<.0001
Error	4136	1850.054	0.447305		
Corrected Total	4153	4350.909			

Root MSE	0.66881	R-Square	0.58355
Dependent Mean	1.93963	Adj R-Sq	0.58184
Coeff Var	34.48122		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	1.465598	0.060376	24.27	<.0001
LN_PRATIO	1	-0.70946	0.157333	-4.51	<.0001
LN_LAG_PAX	1	0.351274	0.015250	23.03	<.0001
RDDINDEX	1	-0.05566	0.006211	-8.96	<.0001
RDD5	1	-0.51413	0.040185	-12.79	<.0001
MON	1	-0.14467	0.039543	-3.66	0.0003
TUE	1	-0.25880	0.039860	-6.49	<.0001
WED	1	-0.10966	0.038406	-2.86	0.0043
THU	1	0.486313	0.040087	12.13	<.0001
FRI	1	1.121762	0.046424	24.16	<.0001
SAT	1	0.194754	0.037739	5.16	<.0001
JAN	1	-0.21402	0.038752	-5.52	<.0001
FEB	1	-0.10569	0.038988	-2.71	0.0067
MAY	1	-0.04781	0.037534	-1.27	0.2028
JUN	1	0.012166	0.038195	0.32	0.7501
JUL	1	0.093539	0.037080	2.52	0.0117
DEC	1	-0.18412	0.038504	-4.78	<.0001
LN_AVGCONN	1	0.161012	0.039831	4.04	<.0001

Figure 36: 2SLS Estimation Results for PoS =‘A’, $MktSegType$=‘EconLate’, $SatStay$=1, $TimeSlot$ = 3

The REG Procedure
Model: MODEL1
Dependent Variable: LN_PAX

Number of Observations Read	4266
Number of Observations Used	4266

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	17	1484.04119	87.29654	176.17	<.0001
Error	4248	2104.94470	0.49551		
Corrected Total	4265	3588.98589			

Root MSE	0.70393	R-Square	0.4135
Dependent Mean	2.40559	Adj R-Sq	0.4112
Coeff Var	29.26211		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	1.56288	0.05617	27.82	<.0001	0
LN_PRATIO	1	0.66009	0.04328	15.25	<.0001	1.62574
LN_LAG_PAX	1	0.17248	0.01464	11.78	<.0001	1.59239
RDDINDEX	1	-0.04319	0.00390	-11.06	<.0001	1.84044
RDD6	1	0.28375	0.04086	6.94	<.0001	1.02860
RDD0	1	-0.62712	0.04753	-13.20	<.0001	1.39562
MON	1	0.75520	0.04377	17.25	<.0001	1.84112
TUE	1	0.66105	0.04196	15.75	<.0001	1.85527
WED	1	0.54725	0.04114	13.30	<.0001	1.81233
THU	1	0.45495	0.04107	11.08	<.0001	1.80178
FRI	1	0.10274	0.04204	2.44	0.0146	1.77979
SAT	1	-0.24329	0.04065	-5.98	<.0001	1.71969
JAN	1	-0.06818	0.03860	-1.77	0.0774	1.06794
JUL	1	0.08320	0.03828	2.17	0.0298	1.07694
AUG	1	0.13476	0.03835	3.51	0.0004	1.07345
SEP	1	0.12176	0.03873	3.14	0.0017	1.07000
OCT	1	0.07017	0.03818	1.84	0.0662	1.06890
LN_AVGCONN	1	0.50087	0.05310	9.43	<.0001	1.16395

Figure 37: Stepwise OLS Estimation Results for PoS='A', $MktSegType$='EconLate', $SatStay$=0, $TimeSlot = 1$

Two-Stage Least Squares Estimation

Model	LN_PAX
Dependent Variable	LN_PAX

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	19	1385.529	72.92257	108.85	<.0001
Error	4246	2844.518	0.669929		
Corrected Total	4265	3588.986			

Root MSE	0.81849	R-Square	0.32754
Dependent Mean	2.40559	Adj R-Sq	0.32454
Coeff Var	34.02451		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	2.305736	0.108599	21.23	<.0001
LN_PRATIO	1	-1.01220	0.202990	-4.99	<.0001
LN_LAG_PAX	1	0.176331	0.017025	10.36	<.0001
RDDINDEX	1	-0.12248	0.010370	-11.81	<.0001
RDD6	1	0.501874	0.053996	9.29	<.0001
RDD0	1	-0.46093	0.058613	-7.86	<.0001
MON	1	0.746207	0.050991	14.63	<.0001
TUE	1	0.676606	0.048895	13.84	<.0001
WED	1	0.553133	0.047914	11.54	<.0001
THU	1	0.400593	0.048226	8.31	<.0001
FRI	1	0.045961	0.049375	0.93	0.3520
SAT	1	-0.36307	0.049333	-7.36	<.0001
JAN	1	-0.09078	0.046521	-1.95	0.0511
FEB	1	0.022064	0.048458	0.46	0.6489
MAY	1	0.015728	0.046550	0.34	0.7355
JUL	1	0.139225	0.046838	2.97	0.0030
AUG	1	0.152563	0.046352	3.29	0.0010
SEP	1	0.166865	0.047100	3.54	0.0004
OCT	1	0.084783	0.046132	1.84	0.0662
LN_AVGCONN	1	0.320479	0.065354	4.90	<.0001

Figure 38: 2SLS Estimation Results for PoS =‘A’, $MktSegType$=‘EconLate’, $SatStay$=0, $TimeSlot$ = 1

The REG Procedure
Model: MODEL1
Dependent Variable: LN_PAX

Number of Observations Read 4293
Number of Observations Used 4293

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	15	1271.21369	84.74758	172.02	<.0001
Error	4277	2107.09919	0.49266		
Corrected Total	4292	3378.31289			

Root MSE	0.70190	R-Square	0.3763
Dependent Mean	2.22525	Adj R-Sq	0.3741
Coeff Var	31.54233		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	2.00937	0.06203	32.39	<.0001	0
LN_PRATIO	1	0.46751	0.04729	9.89	<.0001	1.67525
LN_LAG_PAX	1	0.21651	0.01490	14.53	<.0001	1.30571
RDDINDEX	1	-0.06316	0.00398	-15.86	<.0001	1.93793
RDD6	1	0.27733	0.04049	6.85	<.0001	1.01640
RDD1	1	0.30719	0.04356	7.05	<.0001	1.18617
TUE	1	0.12573	0.03306	3.80	0.0001	1.15963
WED	1	0.12152	0.03260	3.73	0.0002	1.14771
FRI	1	-0.27983	0.03428	-8.16	<.0001	1.20381
SAT	1	-0.41599	0.03454	-12.04	<.0001	1.23766
JAN	1	-0.21577	0.03865	-5.58	<.0001	1.07280
FEB	1	-0.08705	0.03967	-2.19	0.0282	1.05861
MAY	1	-0.16340	0.03834	-4.26	<.0001	1.06986
NOV	1	-0.14732	0.03865	-3.81	0.0001	1.06503
DEC	1	-0.17561	0.03894	-4.51	<.0001	1.07091
LN_AVGCONN	1	0.26749	0.05778	4.63	<.0001	1.06356

Figure 39: Stepwise OLS Estimation Results for PoS=‘A’, $MktSegType$=‘EconLate’, $SatStay$=0, $TimeSlot = 2$

Two-Stage Least Squares Estimation

Model	LN_PAX
Dependent Variable	LN_PAX

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	17	1249.647	73.50866	89.04	<.0001
Error	4275	3529.141	0.825530		
Corrected Total	4292	3378.313			

Root MSE	0.90859	R-Square	0.26150
Dependent Mean	2.22525	Adj R-Sq	0.25856
Coeff Var	40.83075		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	2.922087	0.157227	18.59	<.0001
LN_PRATIO	1	-2.08033	0.376768	-5.52	<.0001
LN_LAG_PAX	1	0.238832	0.019580	12.20	<.0001
RDDINDEX	1	-0.18755	0.018863	-9.94	<.0001
RDD6	1	0.470783	0.059531	7.91	<.0001
RDD1	1	0.245712	0.057093	4.30	<.0001
TUE	1	0.193976	0.043927	4.42	<.0001
WED	1	0.090706	0.042451	2.14	0.0327
FRI	1	-0.29931	0.044473	-6.73	<.0001
SAT	1	-0.49338	0.046111	-10.70	<.0001
JAN	1	-0.13053	0.052822	-2.47	0.0135
FEB	1	-0.11518	0.053293	-2.16	0.0307
MAY	1	-0.07927	0.052402	-1.51	0.1304
JUL	1	0.125752	0.052867	2.38	0.0174
SEP	1	0.124118	0.052897	2.35	0.0190
NOV	1	-0.15293	0.051740	-2.96	0.0031
DEC	1	-0.17865	0.052100	-3.43	0.0006
LN_AVGCONN	1	0.447831	0.079434	5.64	<.0001

Figure 40: 2SLS Estimation Results for PoS =‘A’, $MktSegType$=‘EconLate’, $SatStay$=0, $TimeSlot$ = 2

```
The REG Procedure
Model: MODEL1
Dependent Variable: LN_PAX

Number of Observations Read        4029
Number of Observations Used        4029
```

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	16	1843.40319	115.21270	204.93	<.0001
Error	4012	2255.53152	0.56220		
Corrected Total	4028	4098.93470			

Root MSE	0.74980	R-Square	0.4497
Dependent Mean	1.74991	Adj R-Sq	0.4475
Coeff Var	42.84788		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	2.09352	0.05572	37.58	<.0001	0
LN_PRATIO	1	0.54950	0.04061	13.53	<.0001	1.38746
LN_LAG_PAX	1	0.16539	0.01596	10.36	<.0001	1.43213
PUBHOL	1	-0.15515	0.08221	-1.89	0.0592	1.16080
RDDINDEX	1	-0.10055	0.00393	-25.58	<.0001	1.55145
RDD6	1	0.28031	0.04406	6.36	<.0001	1.01439
MON	1	0.37816	0.04528	8.35	<.0001	1.68943
TUE	1	0.12286	0.04435	2.77	0.0056	1.74955
WED	1	-0.19903	0.04411	-4.51	<.0001	1.71580
THU	1	-0.21230	0.04403	-4.82	<.0001	1.71673
FRI	1	-0.38430	0.04527	-8.49	<.0001	1.69361
SAT	1	-0.63921	0.04665	-13.70	<.0001	1.73015
JAN	1	-0.14838	0.04328	-3.43	0.0006	1.04565
MAY	1	-0.10352	0.04240	-2.44	0.0147	1.05372
JUL	1	0.08491	0.04107	2.07	0.0388	1.04740
DEC	1	-0.12750	0.04234	-3.01	0.0026	1.05569
LN_AVGCONN	1	0.21555	0.04234	5.09	<.0001	1.07171

Figure 41: Stepwise OLS Estimation Results for PoS=‘A’, $MktSegType$=‘EconLate’, $SatStay$=0, $TimeSlot = 3$

Two-Stage Least Squares Estimation

Model	LN_PAX
Dependent Variable	LN_PAX

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	20	1764.477	88.22385	99.26	<.0001
Error	4008	3562.386	0.888819		
Corrected Total	4028	4098.935			

Root MSE	0.94277	R-Square	0.33124
Dependent Mean	1.74991	Adj R-Sq	0.32790
Coeff Var	53.87558		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	2.652387	0.111767	23.73	<.0001
LN_PRATIO	1	-1.43476	0.303166	-4.73	<.0001
LN_LAG_PAX	1	0.187124	0.020368	9.19	<.0001
PUBHOL	1	0.056983	0.108450	0.53	0.5993
RDDINDEX	1	-0.18933	0.014243	-13.29	<.0001
RDD6	1	0.532477	0.067163	7.93	<.0001
MON	1	0.481197	0.059022	8.15	<.0001
TUE	1	0.178026	0.056429	3.15	0.0016
WED	1	-0.12178	0.056744	-2.15	0.0319
THU	1	-0.05487	0.060240	-0.91	0.3625
FRI	1	-0.19036	0.064035	-2.97	0.0030
SAT	1	-0.54453	0.060406	-9.01	<.0001
JAN	1	-0.29438	0.062506	-4.71	<.0001
FEB	1	-0.23285	0.066319	-3.51	0.0005
MAY	1	-0.22169	0.060047	-3.69	0.0002
JUN	1	-0.07680	0.059112	-1.30	0.1939
JUL	1	0.080444	0.055777	1.44	0.1493
OCT	1	-0.22070	0.066347	-3.33	0.0009
NOV	1	-0.29266	0.071331	-4.10	<.0001
DEC	1	-0.25502	0.060418	-4.22	<.0001
LN_AVGCONN	1	0.381369	0.059102	6.45	<.0001

Figure 42: 2SLS Estimation Results for PoS='A', $MktSegType$='EconLate', $SatStay$=0, $TimeSlot = 3$

C.6 OLS and 2SLS Results for Inbound Trips, Economy Class Advance Purchases

In the following figures, for each classification group based on $SatStay$ and $TimeSlot$ under PoS='D', $MktSegType$ ='EconAdvn', we first provide the results from the stepwise OLS estimation followed by the results from the 2SLS estimation.

The REG Procedure
Model: MODEL1
Dependent Variable: LN_PAX

Number of Observations Read	1546
Number of Observations Used	1546

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	12	1063.09446	88.59120	330.75	<.0001
Error	1533	410.61290	0.26785		
Corrected Total	1545	1473.70735			

Root MSE	0.51754	R-Square	0.7214
Dependent Mean	2.47751	Adj R-Sq	0.7192
Coeff Var	20.88962		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	1.36064	0.07685	17.71	<.0001	0
LN_PRATIO	1	-0.60696	0.06917	-8.77	<.0001	1.02937
LN_LAG_PAX	1	0.51568	0.02033	25.37	<.0001	2.31937
PUBHOL	1	0.22049	0.08902	2.48	0.0134	1.09673
SUN	1	0.50809	0.04611	11.02	<.0001	1.60966
MON	1	0.32519	0.04514	7.20	<.0001	1.37517
WED	1	-0.43869	0.04760	-9.22	<.0001	1.51037
THU	1	-0.48083	0.04816	-9.98	<.0001	1.50132
FRI	1	-0.43891	0.04778	-9.19	<.0001	1.45882
SEP	1	-0.12250	0.04599	-2.66	0.0078	1.03121
NOV	1	0.17792	0.04738	3.76	0.0002	1.04644
DEC	1	0.13418	0.04754	2.82	0.0048	1.10204
LN_AVGCONN	1	-0.15299	0.06680	-2.29	0.0221	1.02707

Figure 43: Stepwise OLS Estimation Results for PoS='D', $MktSegType$='EconAdvn', $SatStay$=1, $TimeSlot$ = 1

Two-Stage Least Squares Estimation

Model	LN_PAX
Dependent Variable	LN_PAX

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	13	1092.013	84.00102	234.32	<.0001
Error	1532	549.1948	0.358482		
Corrected Total	1545	1473.707			

Root MSE	0.59873	R-Square	0.66537
Dependent Mean	2.47751	Adj R-Sq	0.66253
Coeff Var	24.16680		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	1.724790	0.098723	17.47	<.0001
LN_PRATIO	1	-2.18323	0.186188	-11.73	<.0001
LN_LAG_PAX	1	0.486938	0.023894	20.38	<.0001
PUBHOL	1	0.316388	0.107940	2.93	0.0034
SUN	1	0.526634	0.061814	8.52	<.0001
MON	1	0.349003	0.060338	5.78	<.0001
WED	1	-0.48702	0.060865	-8.00	<.0001
THU	1	-0.56081	0.061743	-9.08	<.0001
FRI	1	-0.50692	0.061297	-8.27	<.0001
SAT	1	0.067175	0.057183	1.17	0.2403
SEP	1	-0.08965	0.053320	-1.68	0.0929
NOV	1	0.146187	0.054946	2.66	0.0079
DEC	1	0.247206	0.056351	4.39	<.0001
LN_AVGCONN	1	-0.22752	0.077696	-2.93	0.0035

Figure 44: 2SLS Estimation Results for PoS=‘D’, $MktSegType$=‘EconAdvn’, $SatStay$=1, $TimeSlot = 1$

The REG Procedure
Model: MODEL1
Dependent Variable: LN_PAX

Number of Observations Read 1610
Number of Observations Used 1610

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	13	1071.76504	82.44346	383.66	<.0001
Error	1596	342.95598	0.21488		
Corrected Total	1609	1414.72102			

Root MSE	0.46356	R-Square	0.7576
Dependent Mean	3.04298	Adj R-Sq	0.7556
Coeff Var	15.23363		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	1.23514	0.05915	20.88	<.0001	0
LN_PRATIO	1	-0.70876	0.07298	-9.71	<.0001	1.03162
LN_LAG_PAX	1	0.56625	0.01826	31.00	<.0001	2.44663
PUBHOL	1	0.42980	0.08098	5.31	<.0001	1.16129
SUN	1	0.53915	0.04566	11.81	<.0001	1.98142
MON	1	0.37533	0.04092	9.17	<.0001	1.41723
FRI	1	0.07139	0.03716	1.92	0.0549	1.26234
SAT	1	-0.44387	0.04107	-10.81	<.0001	1.35704
JAN	1	-0.15695	0.04162	-3.77	0.0002	1.07007
JUL	1	0.13589	0.04139	3.28	0.0010	1.11014
AUG	1	0.13255	0.04168	3.18	0.0015	1.13225
SEP	1	-0.16430	0.04168	-3.94	<.0001	1.07975
DEC	1	-0.08588	0.04223	-2.03	0.0422	1.10196
LN_AVGCONN	1	0.10993	0.06268	1.75	0.0796	1.09568

Figure 45: Stepwise OLS Estimation Results for PoS='D', $MktSegType$='EconAdvn', $SatStay$=1, $TimeSlot = 2$

Two-Stage Least Squares Estimation

Model	LN_PAX
Dependent Variable	LN_PAX

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	13	1093.580	84.12151	318.27	<.0001
Error	1596	421.8406	0.264311		
Corrected Total	1609	1414.721			

Root MSE	0.51411	R-Square	0.72163
Dependent Mean	3.04298	Adj R-Sq	0.71937
Coeff Var	16.89501		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	1.471180	0.070085	20.99	<.0001
LN_PRATIO	1	-2.10714	0.166999	-12.62	<.0001
LN_LAG_PAX	1	0.559746	0.020267	27.62	<.0001
PUBHOL	1	0.382062	0.089947	4.25	<.0001
SUN	1	0.471397	0.051132	9.22	<.0001
MON	1	0.327658	0.045656	7.18	<.0001
FRI	1	0.025991	0.041486	0.63	0.5311
SAT	1	-0.49765	0.045892	-10.84	<.0001
JAN	1	-0.10264	0.046503	-2.21	0.0274
JUL	1	0.185059	0.046187	4.01	<.0001
AUG	1	0.126038	0.046227	2.73	0.0065
SEP	1	-0.16924	0.046225	-3.66	0.0003
DEC	1	-0.02542	0.047263	-0.54	0.5908
LN_AVGCONN	1	0.079417	0.069584	1.14	0.2539

Figure 46: 2SLS Estimation Results for PoS=‘D’, $MktSegType$=‘EconAdvn’, $SatStay$=1, $TimeSlot = 2$

The REG Procedure
Model: MODEL1
Dependent Variable: LN_PAX

Number of Observations Read 904
Number of Observations Used 904

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	6	139.26206	23.21034	97.97	<.0001
Error	897	212.51616	0.23692		
Corrected Total	903	351.77822			

Root MSE	0.48674	R-Square	0.3959
Dependent Mean	1.46302	Adj R-Sq	0.3918
Coeff Var	33.26967		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	0.77804	0.04451	17.48	<.0001	0
LN_PRATIO	1	-0.06056	0.05375	-1.13	0.2602	1.01523
LN_LAG_PAX	1	0.36399	0.03042	11.96	<.0001	1.46732
SAT	1	0.48155	0.04611	10.44	<.0001	1.47081
FEB	1	0.12910	0.05593	2.31	0.0212	1.03821
NOV	1	0.11430	0.05818	1.96	0.0498	1.03015
DEC	1	0.16689	0.05216	3.20	0.0014	1.07440

Figure 47: Stepwise OLS Estimation Results for PoS='D', $MktSegType$='EconAdvn', $SatStay$=0, $TimeSlot = 1$

Two-Stage Least Squares Estimation

Model	LN_PAX
Dependent Variable	LN_PAX

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	7	148.4142	21.20202	67.31	<.0001
Error	896	282.2150	0.314972		
Corrected Total	903	351.7782			

Root MSE	0.56122	R-Square	0.34464
Dependent Mean	1.46302	Adj R-Sq	0.33952
Coeff Var	38.36055		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	0.941303	0.076682	12.28	<.0001
LN_PRATIO	1	-0.98273	0.184294	-5.33	<.0001
LN_LAG_PAX	1	0.358605	0.035146	10.20	<.0001
SAT	1	0.527897	0.054797	9.63	<.0001
FEB	1	0.059006	0.065780	0.90	0.3699
NOV	1	0.165953	0.067865	2.45	0.0147
DEC	1	0.142163	0.060340	2.36	0.0187
LN_AVGCONN	1	0.023167	0.070781	0.33	0.7435

Figure 48: 2SLS Estimation Results for PoS=‘D’, $MktSegType$=‘EconAdvn’, $SatStay$=0, $TimeSlot = 1$

The REG Procedure
Model: MODEL1
Dependent Variable: LN_PAX

Number of Observations Read	1502
Number of Observations Used	1502

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	12	435.50230	36.29186	136.85	<.0001
Error	1489	394.86343	0.26519		
Corrected Total	1501	830.36574			

Root MSE	0.51496	R-Square	0.5245
Dependent Mean	2.25366	Adj R-Sq	0.5206
Coeff Var	22.85007		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	1.11236	0.05720	19.45	<.0001	0
LN_PRATIO	1	-0.02318	0.04733	-0.49	0.6243	1.08176
LN_LAG_PAX	1	0.43537	0.02131	20.43	<.0001	1.56371
SUN	1	-0.33337	0.05548	-6.01	<.0001	1.52067
MON	1	-0.22591	0.05190	-4.35	<.0001	1.53116
WED	1	0.32030	0.04731	6.77	<.0001	1.66159
THU	1	0.39835	0.04852	8.21	<.0001	1.78406
FRI	1	0.24919	0.04949	5.04	<.0001	1.79254
SAT	1	0.32623	0.04978	6.55	<.0001	1.83945
MAY	1	-0.09970	0.05209	-1.91	0.0558	1.05201
SEP	1	-0.16647	0.04656	-3.58	0.0004	1.05106
DEC	1	0.16793	0.04701	3.57	0.0004	1.07811
LN_AVGCONN	1	0.14097	0.06419	2.20	0.0282	1.08249

Figure 49: Stepwise OLS Estimation Results for PoS='D', $MktSegType$='EconAdvn', $SatStay$=0, $TimeSlot = 2$

Two-Stage Least Squares Estimation

Model	LN_PAX
Dependent Variable	LN_PAX

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	11	436.6900	39.69909	144.64	<.0001
Error	1490	408.9476	0.274461		
Corrected Total	1501	830.3657			

Root MSE	0.52389	R-Square	0.51640
Dependent Mean	2.25366	Adj R-Sq	0.51283
Coeff Var	23.24621		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	1.194186	0.067400	17.72	<.0001
LN_PRATIO	1	-0.35805	0.125466	-2.85	0.0044
LN_LAG_PAX	1	0.438571	0.021419	20.48	<.0001
SUN	1	-0.37556	0.058665	-6.40	<.0001
MON	1	-0.23029	0.052833	-4.36	<.0001
WED	1	0.333753	0.048432	6.89	<.0001
THU	1	0.401082	0.049351	8.13	<.0001
FRI	1	0.214163	0.051307	4.17	<.0001
SAT	1	0.266954	0.053562	4.98	<.0001
SEP	1	-0.12937	0.047911	-2.70	0.0070
DEC	1	0.157969	0.048035	3.29	0.0010
LN_AVGCONN	1	0.148146	0.065341	2.27	0.0235

Figure 50: 2SLS Estimation Results for PoS=‘D’, $MktSegType$=‘EconAdvn’, $SatStay$=0, $TimeSlot = 2$

C.7 OLS and 2SLS Results for Inbound Trips, Economy Class Late Purchases

In the following figures, for each classification group based on $SatStay$ and $TimeSlot$ under PoS ='D', $MktSegType$ ='EconLate', we first provide the results from the stepwise OLS estimation followed by the results from the 2SLS estimation.

The REG Procedure
Model: MODEL1
Dependent Variable: LN_PAX

Number of Observations Read	3491
Number of Observations Used	3491

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	14	3126.99472	223.35677	476.29	<.0001
Error	3476	1630.06276	0.46895		
Corrected Total	3490	4757.05748			

Root MSE	0.68480	R-Square	0.6573
Dependent Mean	1.76568	Adj R-Sq	0.6560
Coeff Var	38.78369		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	1.08835	0.05527	19.69	<.0001	0
LN_PRATIO	1	-0.41133	0.04368	-9.42	<.0001	1.10110
LN_LAG_PAX	1	0.39410	0.01676	23.52	<.0001	2.78289
RDD6	1	0.37698	0.04049	9.31	<.0001	1.01337
PUBHOL	1	0.19680	0.08518	2.31	0.0209	1.13561
SUN	1	0.68251	0.04559	14.97	<.0001	2.13157
MON	1	0.45480	0.04511	10.08	<.0001	1.84036
WED	1	-0.52880	0.04685	-11.29	<.0001	1.90724
THU	1	-0.63164	0.04850	-13.02	<.0001	1.91788
FRI	1	-0.68945	0.04952	-13.92	<.0001	1.96364
SAT	1	-0.41141	0.04473	-9.20	<.0001	1.80011
AUG	1	-0.07185	0.04039	-1.78	0.0754	1.03100
NOV	1	0.08786	0.04047	2.17	0.0300	1.03229
DEC	1	-0.07776	0.04199	-1.85	0.0642	1.03437
LN_AVGCONN	1	0.07664	0.04400	1.74	0.0816	1.04398

Figure 51: Stepwise OLS Estimation Results for PoS ='D', $MktSegType$='EconLate', $SatStay$=1, $TimeSlot$ = 1

Two-Stage Least Squares Estimation

Model	LN_PAX
Dependent Variable	LN_PAX

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	14	3123.413	223.1010	440.69	<.0001
Error	3476	1759.722	0.506249		
Corrected Total	3490	4757.057			

Root MSE	0.71151	R-Square	0.63963
Dependent Mean	1.76568	Adj R-Sq	0.63818
Coeff Var	40.29665		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	1.350151	0.072598	18.60	<.0001
LN_PRATIO	1	-1.13766	0.131312	-8.66	<.0001
LN_LAG_PAX	1	0.328338	0.020677	15.88	<.0001
RDD6	1	0.407351	0.042385	9.61	<.0001
PUBHOL	1	0.175163	0.088584	1.98	0.0481
SUN	1	0.728881	0.048016	15.18	<.0001
MON	1	0.472858	0.046971	10.07	<.0001
WED	1	-0.61240	0.050703	-12.08	<.0001
THU	1	-0.73410	0.053309	-13.77	<.0001
FRI	1	-0.80762	0.055219	-14.63	<.0001
SAT	1	-0.43440	0.046637	-9.31	<.0001
NOV	1	0.097692	0.042083	2.32	0.0203
AUG	1	-0.10480	0.042336	-2.48	0.0134
DEC	1	-0.09160	0.043696	-2.10	0.0361
LN_AVGCONN	1	-0.03957	0.049782	-0.79	0.4268

Figure 52: 2SLS Estimation Results for PoS=‘D’, $MktSegType$=‘EconLate’, $SatStay$=1, $TimeSlot = 1$

The REG Procedure
Model: MODEL1
Dependent Variable: LN_PAX

Number of Observations Read	3680
Number of Observations Used	3680

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	17	3314.33221	194.96072	445.25	<.0001
Error	3662	1603.48615	0.43787		
Corrected Total	3679	4917.81836			

Root MSE	0.66172	R-Square	0.6739
Dependent Mean	2.27345	Adj R-Sq	0.6724
Coeff Var	29.10643		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	1.18798	0.05308	22.38	<.0001	0
LN_PRATIO	1	-0.83079	0.04567	-18.19	<.0001	1.41439
LN_LAG_PAX	1	0.44977	0.01619	27.79	<.0001	2.74432
PUBHOL	1	0.21519	0.07733	2.78	0.0054	1.19899
RDD6	1	0.28114	0.03973	7.08	<.0001	1.04137
SUN	1	0.56317	0.04483	12.56	<.0001	2.22697
MON	1	0.22832	0.04279	5.34	<.0001	1.80072
WED	1	-0.19328	0.04100	-4.71	<.0001	1.74700
THU	1	-0.38840	0.04234	-9.17	<.0001	1.88370
FRI	1	-0.44212	0.04299	-10.28	<.0001	1.92958
SAT	1	-0.85002	0.05040	-16.87	<.0001	1.96756
MAY	1	0.10584	0.03982	2.66	0.0079	1.11466
JUL	1	0.17534	0.03987	4.40	<.0001	1.12035
AUG	1	0.17592	0.03976	4.42	<.0001	1.12313
SEP	1	0.13218	0.03981	3.32	0.0009	1.10197
OCT	1	0.11851	0.03923	3.02	0.0025	1.11056
DEC	1	-0.08129	0.04049	-2.01	0.0448	1.10328
LN_AVGCONN	1	0.33509	0.04575	7.33	<.0001	1.03918

Figure 53: Stepwise OLS Estimation Results for PoS=‘D’, $MktSegType$=‘EconLate’, $SatStay$=1, $TimeSlot = 2$

Two-Stage Least Squares Estimation

Model LN_PAX
Dependent Variable LN_PAX

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	18	3290.108	182.7838	408.59	<.0001
Error	3661	1637.738	0.447347		
Corrected Total	3679	4917.818			

Root MSE	0.66884	R-Square	0.66766
Dependent Mean	2.27345	Adj R-Sq	0.66602
Coeff Var	29.41967		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	1.415990	0.064166	22.07	<.0001
LN_PRATIO	1	-1.23844	0.075400	-16.43	<.0001
LN_LAG_PAX	1	0.381302	0.019185	19.87	<.0001
PUBHOL	1	0.219104	0.078243	2.80	0.0051
RDD6	1	0.323406	0.040631	7.96	<.0001
SUN	1	0.563256	0.045318	12.43	<.0001
MON	1	0.231776	0.043260	5.36	<.0001
WED	1	-0.21971	0.041633	-5.28	<.0001
THU	1	-0.48083	0.044906	-10.71	<.0001
FRI	1	-0.54587	0.046038	-11.86	<.0001
SAT	1	-0.98500	0.054663	-18.02	<.0001
MAY	1	0.146191	0.041382	3.53	0.0004
JUL	1	0.209420	0.041366	5.06	<.0001
AUG	1	0.218161	0.041383	5.27	<.0001
SEP	1	0.162332	0.041253	3.94	<.0001
OCT	1	0.156391	0.040807	3.83	0.0001
NOV	1	0.049093	0.041200	1.19	0.2335
DEC	1	-0.08244	0.041731	-1.98	0.0483
LN_AVGCONN	1	0.327421	0.046253	7.08	<.0001

Figure 54: 2SLS Estimation Results for PoS=‘D’, $MktSegType$=‘EconLate’, $SatStay$=1, $TimeSlot = 2$

The REG Procedure
Model: MODEL1
Dependent Variable: LN_PAX

Number of Observations Read	2871
Number of Observations Used	2871

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	13	164.59276	12.66098	52.83	<.0001
Error	2857	684.73969	0.23967		
Corrected Total	2870	849.33245			

Root MSE	0.48956	R-Square	0.1938
Dependent Mean	1.46340	Adj R-Sq	0.1901
Coeff Var	33.45375		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	1.33563	0.04276	31.23	<.0001	0
LN_PRATIO	1	0.09553	0.02711	3.52	0.0004	1.42552
LN_LAG_PAX	1	0.11243	0.01799	6.25	<.0001	1.15916
PUBHOL	1	-0.27833	0.08101	-3.44	0.0006	1.02684
RDDINDEX	1	-0.02077	0.00307	-6.76	<.0001	1.29579
RDD6	1	0.36453	0.03018	12.08	<.0001	1.02687
RDD7	1	0.31168	0.03235	9.64	<.0001	1.02516
SUN	1	-0.29109	0.03168	-9.19	<.0001	1.23260
MON	1	-0.12148	0.03081	-3.94	<.0001	1.13840
THU	1	0.07274	0.02771	2.63	0.0087	1.15319
SAT	1	0.16280	0.02818	5.78	<.0001	1.41060
FEB	1	0.06309	0.03319	1.90	0.0574	1.01459
AUG	1	-0.08378	0.03488	-2.40	0.0164	1.03558
LN_AVGCONN	1	0.06436	0.03604	1.79	0.0742	1.03187

Figure 55: Stepwise OLS Estimation Results for PoS='D', $MktSegType$='EconLate', $SatStay$=0, $TimeSlot = 1$

Two-Stage Least Squares Estimation

Model	LN_PAX
Dependent Variable	LN_PAX

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	18	163.7653	9.098071	35.66	<.0001
Error	2852	727.5492	0.255101		
Corrected Total	2870	849.3325			

Root MSE	0.50508	R-Square	0.18373
Dependent Mean	1.46340	Adj R-Sq	0.17858
Coeff Var	34.51387		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	1.416766	0.051158	27.69	<.0001
LN_PRATIO	1	-0.26737	0.104331	-2.56	0.0104
LN_LAG_PAX	1	0.115612	0.018593	6.22	<.0001
PUBHOL	1	-0.24048	0.084699	-2.84	0.0046
RDDINDEX	1	-0.03816	0.005775	-6.61	<.0001
RDD6	1	0.375411	0.031275	12.00	<.0001
RDD7	1	0.319532	0.033447	9.55	<.0001
SUN	1	-0.18770	0.043716	-4.29	<.0001
MON	1	-0.09989	0.032448	-3.08	0.0021
THU	1	0.079802	0.028649	2.79	0.0054
SAT	1	0.298336	0.047502	6.28	<.0001
JAN	1	-0.01212	0.035971	-0.34	0.7363
FEB	1	0.042195	0.036796	1.15	0.2516
JUN	1	-0.02073	0.035603	-0.58	0.5604
JUL	1	-0.00296	0.035606	-0.08	0.9337
AUG	1	-0.01401	0.042094	-0.33	0.7393
OCT	1	0.008223	0.034600	0.24	0.8122
NOV	1	0.001024	0.035072	0.03	0.9767
LN_AVGCONN	1	0.032816	0.038170	0.86	0.3900

Figure 56: 2SLS Estimation Results for PoS=‘D’, $MktSegType$=‘EconLate’, $SatStay$=0, $TimeSlot = 1$

The REG Procedure
Model: MODEL1
Dependent Variable: LN_PAX

Number of Observations Read	3731
Number of Observations Used	3731

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	16	1055.05873	65.94117	157.98	<.0001
Error	3714	1550.25052	0.41741		
Corrected Total	3730	2605.30925			

Root MSE	0.64607	R-Square	0.4050
Dependent Mean	2.34415	Adj R-Sq	0.4024
Coeff Var	27.56102		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	2.35286	0.05196	45.28	<.0001	0
LN_PRATIO	1	0.59351	0.03446	17.23	<.0001	1.69150
LN_LAG_PAX	1	0.11177	0.01522	7.34	<.0001	1.40084
PUBHOL	1	-0.86865	0.07635	-11.38	<.0001	1.20006
RDDINDEX	1	-0.02447	0.00355	-6.89	<.0001	1.34567
RDD6	1	0.53719	0.03841	13.98	<.0001	1.03120
RDD7	1	0.37798	0.03883	9.73	<.0001	1.01188
SUN	1	-1.03526	0.04520	-22.90	<.0001	1.84736
MON	1	-0.34436	0.04149	-8.30	<.0001	1.67227
WED	1	0.19017	0.03930	4.84	<.0001	1.77359
THU	1	0.27211	0.03960	6.87	<.0001	1.79869
FRI	1	0.15378	0.03993	3.85	0.0001	1.75369
SAT	1	-0.31704	0.04153	-7.63	<.0001	1.95821
FEB	1	0.10590	0.03847	2.75	0.0059	1.04290
AUG	1	-0.21098	0.03902	-5.41	<.0001	1.13906
SEP	1	0.06550	0.03718	1.76	0.0782	1.04473
DEC	1	-0.11093	0.03820	-2.90	0.0037	1.05167

Figure 57: Stepwise OLS Estimation Results for PoS=‘D’, $MktSegType$=‘EconLate’, $SatStay$=0, $TimeSlot = 2$

Two-Stage Least Squares Estimation

Model	LN_PAX
Dependent Variable	LN_PAX

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	17	938.1495	55.18527	113.05	<.0001
Error	3713	1812.576	0.488170		
Corrected Total	3730	2605.309			

Root MSE	0.69869	R-Square	0.34106
Dependent Mean	2.34415	Adj R-Sq	0.33804
Coeff Var	29.80581		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	2.418327	0.056578	42.74	<.0001
LN_PRATIO	1	-0.28196	0.092608	-3.04	0.0023
LN_LAG_PAX	1	0.118568	0.016486	7.19	<.0001
PUBHOL	1	-0.53951	0.088778	-6.08	<.0001
RDDINDEX	1	-0.06747	0.005672	-11.90	<.0001
RDD6	1	0.614501	0.042220	14.55	<.0001
RDD7	1	0.381340	0.041998	9.08	<.0001
SUN	1	-0.80296	0.053795	-14.93	<.0001
MON	1	-0.38091	0.045033	-8.46	<.0001
WED	1	0.178169	0.042511	4.19	<.0001
THU	1	0.290066	0.042861	6.77	<.0001
FRI	1	0.202926	0.043438	4.67	<.0001
SAT	1	0.030402	0.056049	0.54	0.5876
FEB	1	0.082507	0.042033	1.96	0.0497
JUL	1	0.155290	0.045848	3.39	0.0007
AUG	1	0.104653	0.053135	1.97	0.0490
SEP	1	0.040534	0.040648	1.00	0.3187
DEC	1	-0.02876	0.042690	-0.67	0.5005

Figure 58: 2SLS Estimation Results for PoS=‘D’, $MktSegType$=‘EconLate’, $SatStay$=0, $TimeSlot = 2$

C.8 OLS and 2SLS Results for Outbound Trips, First Class Advance Purchases

In the following figures, for each classification group based on $SatStay$ and $TimeSlot$ under PoS='A', $MktSegType$ ='FrstAdvn', we first provide the results from the stepwise OLS estimation followed by the results from the 2SLS estimation.

```
                              The REG Procedure
                                Model: MODEL1
                         Dependent Variable: LN_PAX

                   Number of Observations Read         623
                   Number of Observations Used         623


                            Analysis of Variance

                                     Sum of           Mean
   Source                   DF      Squares         Square    F Value    Pr > F

   Model                     9    158.14298       17.57144      70.35    <.0001
   Error                   613    153.12012        0.24979
   Corrected Total         622    311.26310


                Root MSE              0.49979    R-Square     0.5081
                Dependent Mean        1.72573    Adj R-Sq     0.5008
                Coeff Var            28.96092


                            Parameter Estimates

                           Parameter       Standard                              Variance
Variable           DF       Estimate          Error    t Value    Pr > |t|      Inflation

Intercept           1        0.73386        0.05764      12.73      <.0001              0
LN_PRATIO           1       -0.32573        0.09949      -3.27      0.0011        1.05303
LN_LAG_PAX          1        0.40495        0.03349      12.09      <.0001        1.74043
PUBHOL              1        0.41691        0.17633       2.36      0.0184        1.10412
TUE                 1       -0.39656        0.12377      -3.20      0.0014        1.12977
FRI                 1        0.51238        0.06609       7.75      <.0001        2.49332
SAT                 1        0.20682        0.05520       3.75      0.0002        1.66518
MAY                 1       -0.13084        0.07888      -1.66      0.0977        1.03995
OCT                 1        0.13133        0.06536       2.01      0.0449        1.03602
NOV                 1        0.16232        0.07066       2.30      0.0219        1.05126
```

Figure 59: Stepwise OLS Estimation Results for PoS='A', $MktSegType$='FrstAdvn', $SatStay$=1, $TimeSlot = 1$

Two-Stage Least Squares Estimation

Model	LN_PAX
Dependent Variable	LN_PAX

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	10	163.9794	16.39794	37.59	<.0001
Error	612	267.0063	0.436285		
Corrected Total	622	311.2631			

Root MSE	0.66052	R-Square	0.38048
Dependent Mean	1.72573	Adj R-Sq	0.37035
Coeff Var	38.27468		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	1.026337	0.112278	9.14	<.0001
LN_PRATIO	1	-2.45294	0.555586	-4.42	<.0001
LN_LAG_PAX	1	0.332662	0.047918	6.94	<.0001
PUBHOL	1	0.675346	0.242280	2.79	0.0055
TUE	1	-0.40914	0.163872	-2.50	0.0128
FRI	1	0.622710	0.091716	6.79	<.0001
SAT	1	0.097646	0.078035	1.25	0.2113
MAY	1	-0.10757	0.104415	-1.03	0.3033
OCT	1	0.134899	0.086389	1.56	0.1189
NOV	1	0.316911	0.101437	3.12	0.0019
LN_AVGCONN	1	-0.07744	0.093328	-0.83	0.4070

Figure 60: 2SLS Estimation Results for PoS=‘A’, $MktSegType$=‘FrstAdvn’, $SatStay$=1, $TimeSlot = 1$

The REG Procedure
Model: MODEL1
Dependent Variable: LN_PAX

Number of Observations Read	818
Number of Observations Used	818

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	14	192.57665	13.75548	56.52	<.0001
Error	803	195.41784	0.24336		
Corrected Total	817	387.99449			

Root MSE	0.49332	R-Square	0.4963
Dependent Mean	1.75158	Adj R-Sq	0.4876
Coeff Var	28.16406		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	1.16922	0.06947	16.83	<.0001	0
LN_PRATIO	1	-0.42249	0.08864	-4.77	<.0001	1.11953
LN_LAG_TOTALPAX	1	0.30242	0.03109	9.73	<.0001	1.68158
SUN	1	-0.48017	0.11084	-4.33	<.0001	1.12839
MON	1	-0.33310	0.10738	-3.10	0.0020	1.19282
TUE	1	-0.44378	0.11355	-3.91	0.0001	1.13424
WED	1	-0.31699	0.06498	-4.88	<.0001	1.34905
FRI	1	0.45937	0.05027	9.14	<.0001	1.67942
SAT	1	0.13505	0.04734	2.85	0.0044	1.44176
JAN	1	-0.37732	0.07305	-5.17	<.0001	1.16269
MAY	1	-0.15620	0.06839	-2.28	0.0226	1.10114
AUG	1	-0.14566	0.06120	-2.38	0.0175	1.13545
SEP	1	-0.18130	0.06265	-2.89	0.0039	1.09871
OCT	1	0.12320	0.06118	2.01	0.0444	1.09778
NOV	1	0.25622	0.06824	3.75	0.0002	1.11269

Figure 61: Stepwise OLS Estimation Results for PoS=‘A’, $MktSegType$=‘FrstAdvn’, $SatStay$=1, $TimeSlot = 2$

Two-Stage Least Squares Estimation

Model	LN_PAX
Dependent Variable	LN_PAX

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	16	194.2028	12.13767	39.28	<.0001
Error	801	247.5167	0.309010		
Corrected Total	817	387.9945			

Root MSE	0.55589	R-Square	0.43965
Dependent Mean	1.75158	Adj R-Sq	0.42846
Coeff Var	31.73635		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	1.306748	0.088676	14.74	<.0001
LN_PRATIO	1	-1.79293	0.374948	-4.78	<.0001
LN_LAG_PAX	1	0.248412	0.037790	6.57	<.0001
SUN	1	-0.50228	0.126115	-3.98	<.0001
MON	1	-0.15957	0.129694	-1.23	0.2189
TUE	1	-0.43889	0.128009	-3.43	0.0006
WED	1	-0.30000	0.073666	-4.07	<.0001
FRI	1	0.592309	0.066326	8.93	<.0001
SAT	1	0.126731	0.053516	2.37	0.0181
JAN	1	-0.46808	0.089564	-5.23	<.0001
MAY	1	-0.16443	0.080997	-2.03	0.0427
JUL	1	-0.12948	0.077591	-1.67	0.0956
AUG	1	-0.29225	0.084678	-3.45	0.0006
SEP	1	-0.16351	0.074672	-2.19	0.0288
OCT	1	0.109477	0.073691	1.49	0.1378
NOV	1	0.446233	0.093486	4.77	<.0001
DEC	1	0.234530	0.084664	2.77	0.0057

Figure 62: 2SLS Estimation Results for PoS=‘A’, $MktSegType$=‘FrstAdvn’, $SatStay$=1, $TimeSlot = 2$

The REG Procedure
Model: MODEL1
Dependent Variable: LN_PAX

Number of Observations Read	538
Number of Observations Used	538

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	7	137.15993	19.59428	78.63	<.0001
Error	530	132.07214	0.24919		
Corrected Total	537	269.23207			

Root MSE	0.49919	R-Square	0.5094
Dependent Mean	1.68632	Adj R-Sq	0.5030
Coeff Var	29.60251		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	0.88987	0.06524	13.64	<.0001	0
LN_PRATIO	1	-0.35067	0.10172	-3.45	0.0006	1.01851
LN_LAG_PAX	1	0.41005	0.03855	10.64	<.0001	1.68351
SUN	1	-0.23270	0.08446	-2.76	0.0061	1.13262
FRI	1	0.42200	0.05589	7.55	<.0001	1.64098
SAT	1	-0.47827	0.14888	-3.21	0.0014	1.04361
JAN	1	-0.17367	0.08386	-2.07	0.0388	1.04490
AUG	1	-0.16284	0.08626	-1.89	0.0596	1.02887

Figure 63: Stepwise OLS Estimation Results for PoS='A', $MktSegType$='FrstAdvn', $SatStay$=1, $TimeSlot = 3$

Two-Stage Least Squares Estimation

Model	LN_PAX
Dependent Variable	LN_PAX

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	9	140.4547	15.60607	37.79	<.0001
Error	528	218.0252	0.412927		
Corrected Total	537	269.2321			

Root MSE	0.64259	R-Square	0.39181
Dependent Mean	1.68632	Adj R-Sq	0.38144
Coeff Var	38.10634		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	1.139980	0.115792	9.85	<.0001
LN_PRATIO	1	-2.24562	0.631558	-3.56	0.0004
LN_LAG_PAX	1	0.369638	0.051125	7.23	<.0001
SUN	1	-0.29069	0.110749	-2.62	0.0089
TUE	1	0.135745	0.223857	0.61	0.5445
FRI	1	0.409905	0.072208	5.68	<.0001
SAT	1	-0.71446	0.205505	-3.48	0.0005
JAN	1	-0.13900	0.109106	-1.27	0.2032
AUG	1	-0.28011	0.120584	-2.32	0.0206
OCT	1	-0.08074	0.102219	-0.79	0.4300

Figure 64: 2SLS Estimation Results for PoS=‘A’, $MktSegType$=‘FrstAdvn’, $SatStay$=1, $TimeSlot = 3$

The REG Procedure
Model: MODEL1
Dependent Variable: LN_PAX

Number of Observations Read	1138
Number of Observations Used	1138

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	9	36.83407	4.09267	15.75	<.0001
Error	1128	293.07554	0.25982		
Corrected Total	1137	329.90961			

Root MSE	0.50972	R-Square	0.1116
Dependent Mean	1.51926	Adj R-Sq	0.1046
Coeff Var	33.55089		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	1.50909	0.04164	36.24	<.0001	0
LN_PRATIO	1	0.08423	0.04918	1.71	0.0871	1.08705
SUN	1	-0.37435	0.06290	-5.95	<.0001	1.15865
MON	1	0.19594	0.04784	4.10	<.0001	1.21755
THU	1	-0.09387	0.04680	-2.01	0.0451	1.21891
FRI	1	-0.26437	0.04881	-5.42	<.0001	1.20088
SAT	1	-0.14829	0.04721	-3.14	0.0017	1.30588
JAN	1	-0.18030	0.06048	-2.98	0.0029	1.01066
MAY	1	-0.12189	0.06288	-1.94	0.0528	1.01300
LN_AVGCONN	1	0.14928	0.04940	3.02	0.0026	1.04049

Figure 65: Stepwise OLS Estimation Results for PoS='A', $MktSegType$='FrstAdvn', $SatStay$=0, $TimeSlot = 1$

Two-Stage Least Squares Estimation

Model	LN_PAX
Dependent Variable	LN_PAX

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	10	36.94187	3.694187	13.40	<.0001
Error	1127	310.7126	0.275699		
Corrected Total	1137	329.9096			

Root MSE	0.52507	R-Square	0.10626
Dependent Mean	1.51926	Adj R-Sq	0.09833
Coeff Var	34.56100		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	1.640847	0.072585	22.61	<.0001
LN_PRATIO	1	-0.32468	0.189920	-1.71	0.0876
SUN	1	-0.42577	0.068949	-6.18	<.0001
MON	1	0.192741	0.049312	3.91	<.0001
THU	1	-0.09212	0.048253	-1.91	0.0565
FRI	1	-0.27013	0.050349	-5.37	<.0001
SAT	1	-0.24090	0.063866	-3.77	0.0002
JAN	1	-0.20083	0.063171	-3.18	0.0015
AUG	1	-0.05666	0.055619	-1.02	0.3085
MAY	1	-0.15468	0.066528	-2.33	0.0202
LN_AVGCONN	1	0.118064	0.052752	2.24	0.0254

Figure 66: 2SLS Estimation Results for PoS =‘A’, $MktSegType$=‘FrstAdvn’, $SatStay$=0, $TimeSlot$ = 1

The REG Procedure
Model: MODEL1
Dependent Variable: LN_PAX

Number of Observations Read 1274
Number of Observations Used 1274

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	12	240.20701	20.01725	47.79	<.0001
Error	1261	528.16980	0.41885		
Corrected Total	1273	768.37681			

Root MSE	0.64719	R-Square	0.3126
Dependent Mean	1.04423	Adj R-Sq	0.3061
Coeff Var	61.97720		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	1.02101	0.05757	17.73	<.0001	0
LN_PRATIO	1	0.10297	0.04935	2.09	0.0371	1.02859
LN_LAG_PAX	1	0.20264	0.02699	7.51	<.0001	1.45525
SUN	1	-0.28331	0.06089	-4.65	<.0001	1.56408
MON	1	0.14227	0.06250	2.28	0.0230	1.57240
WED	1	-0.18020	0.06074	-2.97	0.0031	1.56833
THU	1	-0.37170	0.06407	-5.80	<.0001	1.57756
FRI	1	-0.66188	0.07663	-8.64	<.0001	1.48967
SAT	1	-0.88361	0.08511	-10.38	<.0001	1.46123
JAN	1	-0.32031	0.07114	-4.50	<.0001	1.07244
FEB	1	0.17322	0.06827	2.54	0.0113	1.03475
OCT	1	0.12757	0.06475	1.97	0.0490	1.03899
NOV	1	0.20221	0.06334	3.19	0.0014	1.04109

Figure 67: Stepwise OLS Estimation Results for PoS='A', $MktSegType$='FrstAdvn', $SatStay$=0, $TimeSlot = 2$

Two-Stage Least Squares Estimation

Model	LN_PAX
Dependent Variable	LN_PAX

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	13	246.6608	18.97391	29.29	<.0001
Error	1260	816.2009	0.647778		
Corrected Total	1273	768.3768			

Root MSE	0.80485	R-Square	0.23207
Dependent Mean	1.04423	Adj R-Sq	0.22415
Coeff Var	77.07543		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	1.332094	0.107649	12.37	<.0001
LN_PRATIO	1	-1.19928	0.349619	-3.43	0.0006
LN_LAG_PAX	1	0.180154	0.034099	5.28	<.0001
SUN	1	-0.39370	0.081072	-4.86	<.0001
MON	1	0.213186	0.080049	2.66	0.0078
WED	1	-0.26456	0.078620	-3.37	0.0008
THU	1	-0.46974	0.083618	-5.62	<.0001
FRI	1	-0.82998	0.105157	-7.89	<.0001
SAT	1	-1.09224	0.119354	-9.15	<.0001
JAN	1	-0.41813	0.092199	-4.54	<.0001
FEB	1	0.148012	0.085785	1.73	0.0847
AUG	1	-0.18579	0.084400	-2.20	0.0279
OCT	1	0.082883	0.081881	1.01	0.3116
NOV	1	0.253720	0.081230	3.12	0.0018

Figure 68: 2SLS Estimation Results for PoS =‘A’, $MktSegType$=‘FrstAdvn’, $SatStay$=0, $TimeSlot$ = 2

The REG Procedure
Model: MODEL1
Dependent Variable: LN_PAX

Number of Observations Read	833
Number of Observations Used	833

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	10	60.53061	6.05306	15.50	<.0001
Error	822	320.90931	0.39040		
Corrected Total	832	381.43991			

Root MSE	0.62482	R-Square	0.1587
Dependent Mean	0.75163	Adj R-Sq	0.1485
Coeff Var	83.12818		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	0.71922	0.04606	15.62	<.0001	0
LN_PRATIO	1	0.25426	0.05359	4.74	<.0001	1.01763
LN_LAG_PAX	1	0.10520	0.03424	3.07	0.0022	1.11015
PUBHOL	1	-0.31079	0.14067	-2.21	0.0274	1.03752
SUN	1	-0.18317	0.06174	-2.97	0.0031	1.11116
MON	1	0.18295	0.06237	2.93	0.0035	1.14741
FRI	1	-0.45488	0.07026	-6.47	<.0001	1.13185
MAY	1	-0.15144	0.08681	-1.74	0.0815	1.02505
JUL	1	-0.30500	0.07867	-3.88	0.0001	1.04272
AUG	1	-0.28999	0.08946	-3.24	0.0012	1.03530
LN_AVGCONN	1	0.17253	0.06090	2.83	0.0047	1.01560

Figure 69: Stepwise OLS Estimation Results for PoS='A', $MktSegType$='FrstAdvn', $SatStay$=0, $TimeSlot = 3$

Two-Stage Least Squares Estimation

Model	LN_PAX
Dependent Variable	LN_PAX

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	10	54.10337	5.410337	9.02	<.0001
Error	822	493.3103	0.600134		
Corrected Total	832	381.4399			

Root MSE	0.77468	R-Square	0.09883
Dependent Mean	0.75163	Adj R-Sq	0.08787
Coeff Var	103.06643		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	0.733522	0.057780	12.70	<.0001
LN_PRATIO	1	1.380329	0.695719	1.98	0.0476
LN_LAG_PAX	1	0.074383	0.046490	1.60	0.1100
PUBHOL	1	-0.32400	0.174593	-1.86	0.0638
SUN	1	-0.30047	0.105188	-2.86	0.0044
MON	1	0.096250	0.093933	1.02	0.3058
FRI	1	-0.58689	0.119078	-4.93	<.0001
MAY	1	-0.14231	0.107780	-1.32	0.1871
JUL	1	-0.34561	0.100686	-3.43	0.0006
AUG	1	-0.30541	0.111326	-2.74	0.0062
LN_AVGCONN	1	0.176146	0.075545	2.33	0.0200

Hausman's Specification Test Results

Comparing	To	DF	Statistic	Pr > ChiSq
OLS	2SLS	11	2.64	0.9947

Figure 70: 2SLS Estimation Results for PoS =‘A’, $MktSegType$=‘FrstAdvn’, $SatStay$=0, $TimeSlot$ = 3

C.9 OLS and 2SLS Results for Outbound Trips, First Class Late Purchases

In the following figures, for each classification group based on $SatStay$ and $TimeSlot$ under $PoS =$'A', $MktSegType =$'FrstLate', we first provide the results from the stepwise OLS estimation followed by the results from the 2SLS estimation.

The REG Procedure
Model: MODEL1
Dependent Variable: LN_PAX

Number of Observations Read	1749
Number of Observations Used	1749

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	12	133.60761	11.13397	50.62	<.0001
Error	1736	381.85894	0.21996		
Corrected Total	1748	515.46654			

Root MSE	0.46900	R-Square	0.2592
Dependent Mean	1.44845	Adj R-Sq	0.2541
Coeff Var	32.37979		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	1.20575	0.04759	25.34	<.0001	0
LN_PRATIO	1	0.01451	0.04594	0.32	0.7522	1.41382
LN_LAG_PAX	1	0.13469	0.02281	5.90	<.0001	1.26108
PUBHOL	1	0.61592	0.10729	5.74	<.0001	1.03471
RDD9	1	-0.23581	0.04538	-5.20	<.0001	1.07068
RDD5	1	-0.31826	0.04973	-6.40	<.0001	1.01991
RDD0	1	-0.50440	0.04952	-10.19	<.0001	1.25554
RDDINDEX	1	-0.02887	0.00388	-7.44	<.0001	1.68695
FRI	1	0.40149	0.03031	13.25	<.0001	1.53088
SAT	1	0.34694	0.02899	11.97	<.0001	1.40973
JUL	1	0.06181	0.03588	1.72	0.0851	1.01867
DEC	1	-0.10658	0.03986	-2.67	0.0076	1.03211
LN_AVGCONN	1	0.10622	0.03794	2.80	0.0052	1.05736

Figure 71: Stepwise OLS Estimation Results for $PoS =$'A', $MktSegType=$'FrstLate', $SatStay=1$, $TimeSlot = 1$

Two-Stage Least Squares Estimation

Model	LN_PAX
Dependent Variable	LN_PAX

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	16	135.5342	8.470889	36.82	<.0001
Error	1732	398.4342	0.230043		
Corrected Total	1748	515.4665			

Root MSE	0.47963	R-Square	0.25382
Dependent Mean	1.44845	Adj R-Sq	0.24693
Coeff Var	33.11324		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	1.349688	0.074667	18.08	<.0001
LN_PRATIO	1	-0.39303	0.172798	-2.27	0.0231
LN_LAG_PAX	1	0.137154	0.023434	5.85	<.0001
PUBHOL	1	0.601942	0.111076	5.42	<.0001
RDD9	1	-0.25290	0.046966	-5.38	<.0001
RDD5	1	-0.31765	0.051049	-6.22	<.0001
RDD0	1	-0.50575	0.050971	-9.92	<.0001
RDDINDEX	1	-0.04540	0.008037	-5.65	<.0001
MON	1	-0.00226	0.048890	-0.05	0.9632
WED	1	-0.04456	0.054863	-0.81	0.4168
FRI	1	0.426512	0.038317	11.13	<.0001
SAT	1	0.352754	0.035032	10.07	<.0001
FEB	1	-0.02667	0.045307	-0.59	0.5561
JUN	1	-0.05807	0.040805	-1.42	0.1549
JUL	1	0.043335	0.037554	1.15	0.2487
DEC	1	-0.12845	0.041824	-3.07	0.0022
LN_AVGCONN	1	0.074767	0.043634	1.71	0.0868

Figure 72: 2SLS Estimation Results for PoS=‘A’, $MktSegType$=‘FrstLate’, $SatStay$=1, $TimeSlot = 1$

The REG Procedure
Model: MODEL1
Dependent Variable: LN_PAX

Number of Observations Read	1976
Number of Observations Used	1976

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	10	222.45288	22.24529	96.14	<.0001
Error	1965	454.67910	0.23139		
Corrected Total	1975	677.13197			

Root MSE	0.48103	R-Square	0.3285
Dependent Mean	1.53766	Adj R-Sq	0.3251
Coeff Var	31.28313		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	1.14362	0.03839	29.79	<.0001	0
LN_PRATIO	1	0.00523	0.04350	0.12	0.9042	1.30927
LN_LAG_PAX	1	0.17756	0.02178	8.15	<.0001	1.34776
PUBHOL	1	0.30369	0.08453	3.59	0.0003	1.03174
RDD5	1	-0.34710	0.05149	-6.74	<.0001	1.01536
RDD9	1	-0.28905	0.04727	-6.12	<.0001	1.05424
RDDINDEX	1	-0.02161	0.00324	-6.67	<.0001	1.36342
FRI	1	0.51669	0.03026	17.08	<.0001	1.54194
SAT	1	0.46249	0.02843	16.27	<.0001	1.41268
JUL	1	0.13043	0.03622	3.60	0.0003	1.02374
DEC	1	-0.13009	0.03895	-3.34	0.0009	1.02428

Figure 73: Stepwise OLS Estimation Results for PoS='A', $MktSegType$='FrstLate', $SatStay$=1, $TimeSlot = 2$

Two-Stage Least Squares Estimation

Model	LN_PAX
Dependent Variable	LN_PAX

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	12	225.6162	18.80135	75.73	<.0001
Error	1963	487.3291	0.248257		
Corrected Total	1975	677.1320			

Root MSE	0.49825	R-Square	0.31646
Dependent Mean	1.53766	Adj R-Sq	0.31228
Coeff Var	32.40336		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	1.350632	0.069067	19.56	<.0001
LN_PRATIO	1	-0.52656	0.156951	-3.35	0.0008
LN_LAG_PAX	1	0.163246	0.022918	7.12	<.0001
PUBHOL	1	0.232031	0.089820	2.58	0.0099
RDD5	1	-0.33494	0.053457	-6.27	<.0001
RDD9	1	-0.30847	0.049260	-6.26	<.0001
RDDINDEX	1	-0.04084	0.006336	-6.45	<.0001
SUN	1	-0.12712	0.057192	-2.22	0.0264
TUE	1	-0.09534	0.056141	-1.70	0.0896
FRI	1	0.521963	0.032635	15.99	<.0001
SAT	1	0.461106	0.030792	14.97	<.0001
JUL	1	0.113402	0.037894	2.99	0.0028
DEC	1	-0.12077	0.040473	-2.98	0.0029

Figure 74: 2SLS Estimation Results for PoS=‘A’, $MktSegType$=‘FrstLate’, $SatStay$=1, $TimeSlot = 2$

The REG Procedure
Model: MODEL1
Dependent Variable: LN_PAX

Number of Observations Read	2085
Number of Observations Used	2085

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	16	356.02685	22.25168	92.04	<.0001
Error	2068	499.95108	0.24176		
Corrected Total	2084	855.97793			

Root MSE	0.49169	R-Square	0.4159
Dependent Mean	1.58376	Adj R-Sq	0.4114
Coeff Var	31.04551		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	1.64394	0.04993	32.93	<.0001	0
LN_PRATIO	1	0.09952	0.04327	2.30	0.0215	1.72183
LN_LAG_PAX	1	0.16443	0.02114	7.78	<.0001	1.55161
PUBHOL	1	-0.16361	0.08500	-1.92	0.0544	1.08615
RDD5	1	-0.41061	0.04532	-9.06	<.0001	1.02802
RDD9	1	-0.23606	0.04412	-5.35	<.0001	1.09345
RDDINDEX	1	-0.03557	0.00363	-9.78	<.0001	1.67854
SUN	1	-0.45469	0.03948	-11.52	<.0001	1.69274
MON	1	-0.43732	0.05139	-8.51	<.0001	1.27396
TUE	1	-0.40413	0.04780	-8.46	<.0001	1.32351
WED	1	-0.30325	0.03726	-8.14	<.0001	1.48689
FRI	1	0.29001	0.03287	8.82	<.0001	1.81377
SAT	1	-0.33642	0.05235	-6.43	<.0001	1.37165
FEB	1	-0.08166	0.03883	-2.10	0.0356	1.04139
JUL	1	0.06413	0.03599	1.78	0.0749	1.04569
DEC	1	-0.09011	0.03754	-2.40	0.0165	1.04433
LN_AVGCONN	1	0.11852	0.04255	2.79	0.0054	1.08996

Figure 75: Stepwise OLS Estimation Results for PoS='A', $MktSegType$='FrstLate', $SatStay$=1, $TimeSlot = 3$

Two-Stage Least Squares Estimation

Model	LN_PAX
Dependent Variable	LN_PAX

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	18	355.0035	19.72241	81.13	<.0001
Error	2066	502.2257	0.243091		
Corrected Total	2084	855.9779			

Root MSE	0.49304	R-Square	0.41413
Dependent Mean	1.58376	Adj R-Sq	0.40902
Coeff Var	31.13112		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	1.653847	0.054265	30.48	<.0001
LN_PRATIO	1	-0.03941	0.175368	-0.22	0.8222
LN_LAG_PAX	1	0.167483	0.021730	7.71	<.0001
PUBHOL	1	-0.12331	0.095105	-1.30	0.1949
RDD5	1	-0.41929	0.046792	-8.96	<.0001
RDD9	1	-0.24395	0.045527	-5.36	<.0001
RDDINDEX	1	-0.04189	0.008431	-4.97	<.0001
SUN	1	-0.41731	0.061863	-6.75	<.0001
MON	1	-0.43403	0.052091	-8.33	<.0001
TUE	1	-0.40321	0.048031	-8.39	<.0001
WED	1	-0.30658	0.037612	-8.15	<.0001
FRI	1	0.315595	0.045603	6.92	<.0001
SAT	1	-0.31286	0.059430	-5.26	<.0001
FEB	1	-0.08177	0.041020	-1.99	0.0463
JUL	1	0.080967	0.038366	2.11	0.0349
NOV	1	0.037144	0.040796	0.91	0.3627
OCT	1	0.012044	0.038223	0.32	0.7527
DEC	1	-0.07560	0.039217	-1.93	0.0540
LN_AVGCONN	1	0.124596	0.043101	2.89	0.0039

Hausman's Specification Test Results

Comparing	To	DF	Statistic	Pr > ChiSq
OLS	2SLS	19	0.70	1.0000

Figure 76: 2SLS Estimation Results for PoS=‘A’, $MktSegType$=‘FrstLate’, $SatStay$=1, $TimeSlot$ = 3

The REG Procedure
Model: MODEL1
Dependent Variable: LN_PAX

Number of Observations Read	2704
Number of Observations Used	2704

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	13	1408.83111	108.37162	133.97	<.0001
Error	2690	2175.96789	0.80891		
Corrected Total	2703	3584.79900			

Root MSE	0.89939	R-Square	0.3930
Dependent Mean	1.95687	Adj R-Sq	0.3901
Coeff Var	45.96089		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	2.15401	0.07607	28.32	<.0001	0
LN_PRATIO	1	0.77782	0.05493	14.16	<.0001	1.26594
LN_LAG_PAX	1	0.11303	0.01772	6.38	<.0001	1.43681
PUBHOL	1	-0.71340	0.10010	-7.13	<.0001	1.07767
RDD6	1	0.65338	0.06209	10.52	<.0001	1.02252
RDD0	1	-0.89312	0.07176	-12.45	<.0001	1.38168
RDDINDEX	1	-0.11735	0.00605	-19.39	<.0001	1.75399
MON	1	0.16026	0.04571	3.51	0.0005	1.07056
FRI	1	-0.22455	0.04716	-4.76	<.0001	1.08880
JUN	1	0.13520	0.06116	2.21	0.0272	1.04923
AUG	1	-0.52816	0.06175	-8.55	<.0001	1.11922
SEP	1	0.11353	0.06105	1.86	0.0630	1.04901
DEC	1	-0.15731	0.06102	-2.58	0.0100	1.05937
LN_AVGCONN	1	0.71502	0.06017	11.88	<.0001	1.04516

Figure 77: Stepwise OLS Estimation Results for PoS=‘A’, $MktSegType$=‘FrstLate’, $SatStay$=0, $TimeSlot = 1$

Two-Stage Least Squares Estimation

Model	LN_PAX
Dependent Variable	LN_PAX

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	13	1254.475	96.49806	72.89	<.0001
Error	2690	3561.486	1.323972		
Corrected Total	2703	3584.799			

Root MSE	1.15064	R-Square	0.26048
Dependent Mean	1.95687	Adj R-Sq	0.25691
Coeff Var	58.80006		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	2.618181	0.158093	16.56	<.0001
LN_PRATIO	1	-1.49545	0.614204	-2.43	0.0150
LN_LAG_PAX	1	0.076596	0.024684	3.10	0.0019
PUBHOL	1	-0.40642	0.152278	-2.67	0.0077
RDD6	1	0.886660	0.101143	8.77	<.0001
RDD0	1	-0.95480	0.093284	-10.24	<.0001
RDDINDEX	1	-0.20256	0.024147	-8.39	<.0001
MON	1	0.143334	0.058658	2.44	0.0146
FRI	1	-0.24324	0.060536	-4.02	<.0001
JUN	1	0.000682	0.086176	0.01	0.9937
AUG	1	0.088026	0.183291	0.48	0.6311
SEP	1	0.008348	0.083045	0.10	0.9199
DEC	1	-0.05898	0.082407	-0.72	0.4742
LN_AVGCONN	1	0.536399	0.090687	5.91	<.0001

Figure 78: 2SLS Estimation Results for PoS =‘A’, $MktSegType$=‘FrstLate’, $SatStay$=0, $TimeSlot$ = 1

The REG Procedure
Model: MODEL1
Dependent Variable: LN_PAX

Number of Observations Read	3472
Number of Observations Used	3472

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	12	1116.10500	93.00875	171.29	<.0001
Error	3459	1878.23318	0.54300		
Corrected Total	3471	2994.33818			

Root MSE	0.73688	R-Square	0.3727
Dependent Mean	1.31003	Adj R-Sq	0.3706
Coeff Var	56.24931		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	1.74089	0.05044	34.51	<.0001	0
LN_PRATIO	1	0.37396	0.03358	11.14	<.0001	1.21793
LN_LAG_PAX	1	0.12150	0.01656	7.34	<.0001	1.33334
PUBHOL	1	-0.45417	0.08456	-5.37	<.0001	1.05426
RDD6	1	0.32463	0.04541	7.15	<.0001	1.00612
RDDINDEX	1	-0.09228	0.00380	-24.28	<.0001	1.30766
SUN	1	-0.36628	0.03723	-9.84	<.0001	1.17971
THU	1	-0.09161	0.03881	-2.36	0.0183	1.13302
FRI	1	-0.55856	0.04227	-13.21	<.0001	1.21719
SAT	1	-0.71920	0.04512	-15.94	<.0001	1.31561
AUG	1	-0.28190	0.04310	-6.54	<.0001	1.03814
DEC	1	-0.14044	0.04571	-3.07	0.0021	1.02279
LN_AVGCONN	1	0.35371	0.04472	7.91	<.0001	1.05213

Figure 79: Stepwise OLS Estimation Results for PoS='A', $MktSegType$='FrstLate', $SatStay$=0, $TimeSlot = 2$

Two-Stage Least Squares Estimation

Model	LN_PAX
Dependent Variable	LN_PAX

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	14	1054.878	75.34842	77.31	<.0001
Error	3457	3369.400	0.974660		
Corrected Total	3471	2994.338			

Root MSE	0.98725	R-Square	0.23843
Dependent Mean	1.31003	Adj R-Sq	0.23535
Coeff Var	75.36060		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	1.646822	0.074331	22.16	<.0001
LN_PRATIO	1	-1.38932	0.557974	-2.49	0.0128
LN_LAG_PAX	1	0.138502	0.022852	6.06	<.0001
PUBHOL	1	-0.13542	0.151432	-0.89	0.3713
RDD6	1	0.423182	0.068344	6.19	<.0001
RDDINDEX	1	-0.15702	0.021051	-7.46	<.0001
SUN	1	-0.21027	0.069949	-3.01	0.0027
THU	1	-0.12105	0.052922	-2.29	0.0222
FRI	1	-0.52575	0.057514	-9.14	<.0001
SAT	1	-0.35632	0.129208	-2.76	0.0059
JUN	1	-0.07199	0.068780	-1.05	0.2953
JUL	1	0.111783	0.072534	1.54	0.1234
AUG	1	0.030108	0.114307	0.26	0.7923
DEC	1	-0.05073	0.068071	-0.75	0.4562
LN_AVGCONN	1	0.624520	0.104928	5.95	<.0001

Figure 80: 2SLS Estimation Results for PoS =‘A’, $MktSegType$=‘FrstLate’, $SatStay$=0, $TimeSlot = 2$

The REG Procedure
Model: MODEL1
Dependent Variable: LN_PAX

Number of Observations Read	3166
Number of Observations Used	3166

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	13	2002.91017	154.07001	207.96	<.0001
Error	3152	2335.15562	0.74085		
Corrected Total	3165	4338.06579			

Root MSE	0.86073	R-Square	0.4617
Dependent Mean	1.68914	Adj R-Sq	0.4595
Coeff Var	50.95639		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	2.55545	0.05967	42.82	<.0001	0
LN_PRATIO	1	0.45615	0.04858	9.39	<.0001	1.09575
LN_LAG_PAX	1	0.12846	0.01723	7.45	<.0001	1.58107
PUBHOL	1	-0.85669	0.09937	-8.62	<.0001	1.06459
RDD6	1	0.55453	0.05423	10.23	<.0001	1.00676
RDDINDEX	1	-0.13065	0.00480	-27.20	<.0001	1.39959
SUN	1	-0.44355	0.04417	-10.04	<.0001	1.16188
THU	1	-0.20347	0.04492	-4.53	<.0001	1.13361
FRI	1	-1.06726	0.05275	-20.23	<.0001	1.31520
SAT	1	-1.74291	0.07983	-21.83	<.0001	1.36841
JUL	1	-0.09366	0.05340	-1.75	0.0795	1.04210
AUG	1	-0.46250	0.05462	-8.47	<.0001	1.06079
DEC	1	-0.20726	0.05545	-3.74	0.0002	1.03540
LN_AVGCONN	1	0.19069	0.05468	3.49	0.0005	1.02787

Figure 81: Stepwise OLS Estimation Results for PoS=‘A’, $MktSegType$=‘FrstLate’, $SatStay$=0, $TimeSlot = 3$

Two-Stage Least Squares Estimation

Model	LN_PAX
Dependent Variable	LN_PAX

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	13	1939.517	149.1936	119.73	<.0001
Error	3152	3927.772	1.246120		
Corrected Total	3165	4338.066			

Root MSE	1.11630	R-Square	0.33056
Dependent Mean	1.68914	Adj R-Sq	0.32780
Coeff Var	66.08667		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	2.729610	0.136013	20.07	<.0001
LN_PRATIO	1	-1.79636	1.448000	-1.24	0.2149
LN_LAG_PAX	1	0.119041	0.023154	5.14	<.0001
PUBHOL	1	-0.89655	0.131391	-6.82	<.0001
RDD6	1	0.642956	0.090400	7.11	<.0001
RDDINDEX	1	-0.18545	0.035740	-5.19	<.0001
SUN	1	-0.35386	0.081237	-4.36	<.0001
THU	1	-0.22029	0.059250	-3.72	0.0002
FRI	1	-1.09500	0.070691	-15.49	<.0001
SAT	1	-1.78620	0.107199	-16.66	<.0001
JUL	1	-0.30565	0.152751	-2.00	0.0455
AUG	1	-0.63263	0.130213	-4.86	<.0001
DEC	1	-0.12746	0.088311	-1.44	0.1490
LN_AVGCONN	1	0.177127	0.071449	2.48	0.0132

Hausman's Specification Test Results

Comparing	To	DF	Statistic	Pr > ChiSq
OLS	2SLS	14	2.42	0.9997

Figure 82: 2SLS Estimation Results for PoS =‘A’, $MktSegType$=‘FrstLate’, $SatStay$=0, $TimeSlot$ = 3

C.10 OLS and 2SLS Results for Inbound Trips, First Class Advance Purchases

In the following figures, for each classification group based on $SatStay$ and $TimeSlot$ under PoS =‘D’, $MktSegType$ =‘FrstAdvn’, we first provide the results from the stepwise OLS estimation followed by the results from the 2SLS estimation.

The REG Procedure
Model: MODEL1
Dependent Variable: LN_PAX

Number of Observations Read	696
Number of Observations Used	696

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	6	50.89396	8.48233	32.97	<.0001
Error	689	177.27032	0.25729		
Corrected Total	695	228.16428			

Root MSE	0.50723	R-Square	0.2231
Dependent Mean	0.44406	Adj R-Sq	0.2163
Coeff Var	114.22564		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	0.15595	0.02941	5.30	<.0001	0
LN_PRATIO	1	0.10023	0.05580	1.80	0.0729	1.00483
LN_LAG_PAX	1	0.12509	0.03596	3.48	0.0005	1.15672
PUBHOL	1	0.64257	0.10771	5.97	<.0001	1.08685
SUN	1	0.46593	0.04993	9.33	<.0001	1.24505
MON	1	0.34655	0.05243	6.61	<.0001	1.16279
MAY	1	0.16813	0.07549	2.23	0.0263	1.02788

Figure 83: Stepwise OLS Estimation Results for PoS =‘D’, $MktSegType$=‘FrstAdvn’, $SatStay$=1, $TimeSlot$ = 1

Two-Stage Least Squares Estimation

Model	LN_PAX
Dependent Variable	LN_PAX

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	8	50.99244	6.374055	23.78	<.0001
Error	687	184.1218	0.268008		
Corrected Total	695	228.1643			

Root MSE	0.51770	R-Square	0.21688
Dependent Mean	0.44406	Adj R-Sq	0.20776
Coeff Var	116.58144		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	0.151541	0.044512	3.40	0.0007
LN_PRATIO	1	0.389602	0.284890	1.37	0.1719
LN_LAG_PAX	1	0.132226	0.037470	3.53	0.0004
PUBHOL	1	0.629382	0.111988	5.62	<.0001
SUN	1	0.444063	0.054753	8.11	<.0001
MON	1	0.324593	0.057164	5.68	<.0001
WED	1	-0.03303	0.074477	-0.44	0.6576
THU	1	-0.01541	0.085309	-0.18	0.8567
MAY	1	0.157264	0.077704	2.02	0.0434

Hausman's Specification Test Results

Comparing	To	DF	Statistic	Pr > ChiSq
OLS	2SLS	9	1.13	0.9991

Figure 84: 2SLS Estimation Results for PoS='D', $MktSegType$='FrstAdvn', $SatStay$=1, $TimeSlot = 1$

The REG Procedure
Model: MODEL1
Dependent Variable: LN_PAX

Number of Observations Read	659
Number of Observations Used	659

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	8	88.53684	11.06711	43.67	<.0001
Error	650	164.71663	0.25341		
Corrected Total	658	253.25347			

Root MSE	0.50340	R-Square	0.3496
Dependent Mean	1.35459	Adj R-Sq	0.3416
Coeff Var	37.16256		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	0.78521	0.05360	14.65	<.0001	0
LN_PRATIO	1	0.00249	0.07109	0.04	0.9721	1.03711
LN_LAG_TOTALPAX	1	0.31837	0.03652	8.72	<.0001	1.30385
BANK_HOL	1	0.33006	0.09812	3.36	0.0008	1.08787
SUN	1	0.43451	0.04875	8.91	<.0001	1.33489
WED	1	-0.12881	0.06621	-1.95	0.0521	1.08239
AUG	1	-0.15520	0.06865	-2.26	0.0241	1.04458
SEP	1	-0.11924	0.07124	-1.67	0.0947	1.02629
NOV	1	0.19148	0.07363	2.60	0.0095	1.06051

Figure 85: Stepwise OLS Estimation Results for PoS='D', $MktSegType$='FrstAdvn', $SatStay$=1, $TimeSlot = 2$

Two-Stage Least Squares Estimation

Model	LN_PAX
Dependent Variable	LN_PAX

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	9	91.24036	10.13782	26.19	<.0001
Error	649	251.1978	0.387054		
Corrected Total	658	253.2535			

Root MSE	0.62214	R-Square	0.26644
Dependent Mean	1.35459	Adj R-Sq	0.25627
Coeff Var	45.92816		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	0.869665	0.079163	10.99	<.0001
LN_PRATIO	1	-1.33870	0.517886	-2.58	0.0100
LN_LAG_PAX	1	0.282734	0.047067	6.01	<.0001
PUBHOL	1	0.466992	0.132962	3.51	0.0005
SUN	1	0.658983	0.104165	6.33	<.0001
WED	1	-0.09646	0.086174	-1.12	0.2634
FRI	1	0.211004	0.095677	2.21	0.0278
AUG	1	-0.21119	0.087403	-2.42	0.0160
SEP	1	-0.14891	0.088744	-1.68	0.0938
NOV	1	0.313374	0.101923	3.07	0.0022

Figure 86: 2SLS Estimation Results for PoS=‘D’, $MktSegType$=‘FrstAdvn’, $SatStay$=1, $TimeSlot = 2$

The REG Procedure
Model: MODEL1
Dependent Variable: LN_PAX

Number of Observations Read	356
Number of Observations Used	356

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	7	8.40590	1.20084	5.51	<.0001
Error	348	75.85271	0.21797		
Corrected Total	355	84.25861			

Root MSE	0.46687	R-Square	0.0998
Dependent Mean	0.36959	Adj R-Sq	0.0817
Coeff Var	126.32058		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	0.13398	0.05950	2.25	0.0250	0
LN_PRATIO	1	0.08414	0.10335	0.81	0.4161	1.01000
WED	1	0.14553	0.08402	1.73	0.0841	1.59424
THU	1	0.32092	0.07930	4.05	<.0001	1.70803
FRI	1	0.27732	0.07834	3.54	0.0005	1.73069
SAT	1	0.30724	0.07854	3.91	0.0001	1.72359
AUG	1	-0.20409	0.10808	-1.89	0.0598	1.01158
NOV	1	0.25040	0.07884	3.18	0.0016	1.01242

Figure 87: Stepwise OLS Estimation Results for PoS='D', $MktSegType$='FrstAdvn', $SatStay$=0, $TimeSlot = 1$

Two-Stage Least Squares Estimation

Model	LN_PAX
Dependent Variable	LN_PAX

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	7	8.768409	1.252630	5.65	<.0001
Error	348	77.09521	0.221538		
Corrected Total	355	84.25861			

Root MSE	0.47068	R-Square	0.10212
Dependent Mean	0.36959	Adj R-Sq	0.08406
Coeff Var	127.35097		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	0.141260	0.060254	2.34	0.0196
LN_PRATIO	1	0.330890	0.218729	1.51	0.1312
WED	1	0.139658	0.084831	1.65	0.1006
THU	1	0.311323	0.080298	3.88	0.0001
FRI	1	0.273493	0.079034	3.46	0.0006
SAT	1	0.314397	0.079373	3.96	<.0001
AUG	1	-0.20332	0.108961	-1.87	0.0629
NOV	1	0.248387	0.079495	3.12	0.0019

Figure 88: 2SLS Estimation Results for PoS=‘D’, $MktSegType$=‘FrstAdvn’, $SatStay$=0, $TimeSlot = 1$

The REG Procedure
Model: MODEL1
Dependent Variable: LN_PAX

Number of Observations Read 1029
Number of Observations Used 1029

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	12	168.35868	14.02989	33.31	<.0001
Error	1016	427.87454	0.42114		
Corrected Total	1028	596.23322			

Root MSE	0.64895	R-Square	0.2824
Dependent Mean	1.04216	Adj R-Sq	0.2739
Coeff Var	62.26969		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	0.90656	0.06154	14.73	<.0001	0
LN_PRATIO	1	0.04353	0.07013	0.62	0.5350	1.07538
LN_LAG_PAX	1	0.13215	0.03095	4.27	<.0001	1.19430
PUBHOL	1	-0.82047	0.20329	-4.04	<.0001	1.06787
SUN	1	-0.60507	0.09351	-6.47	<.0001	1.37255
MON	1	-0.45228	0.08932	-5.06	<.0001	1.39783
WED	1	0.19248	0.06872	2.80	0.0052	1.70857
THU	1	0.16580	0.06708	2.47	0.0136	1.75387
FRI	1	0.27210	0.06926	3.93	<.0001	1.72093
SAT	1	-0.58565	0.08103	-7.23	<.0001	1.64058
AUG	1	-0.38369	0.08303	-4.62	<.0001	1.02532
NOV	1	0.16281	0.06885	2.36	0.0182	1.01608
LN_AVGCONN	1	0.23155	0.06367	3.64	0.0003	1.00996

Figure 89: Stepwise OLS Estimation Results for PoS='D', $MktSegType$='FrstAdvn', $SatStay$=0, $TimeSlot = 2$

Two-Stage Least Squares Estimation

Model	LN_PAX
Dependent Variable	LN_PAX

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	12	184.5974	15.38311	6.64	<.0001
Error	1016	2355.080	2.317992		
Corrected Total	1028	596.2332			

Root MSE	1.52250	R-Square	0.07269
Dependent Mean	1.04216	Adj R-Sq	0.06173
Coeff Var	146.09026		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	1.286931	0.203712	6.32	<.0001
LN_PRATIO	1	4.787753	1.799922	2.66	0.0079
LN_LAG_PAX	1	-0.02111	0.092871	-0.23	0.8203
PUBHOL	1	-1.57443	0.555515	-2.83	0.0047
SUN	1	-1.04694	0.275682	-3.80	0.0002
MON	1	-0.54845	0.212689	-2.58	0.0101
WED	1	0.148227	0.162081	0.91	0.3607
THU	1	0.189476	0.157624	1.20	0.2296
FRI	1	0.378127	0.167348	2.26	0.0241
SAT	1	-1.74883	0.478806	-3.65	0.0003
AUG	1	-0.65797	0.220639	-2.98	0.0029
NOV	1	0.213967	0.162670	1.32	0.1887
LN_AVGCONN	1	0.124125	0.154793	0.80	0.4228

Figure 90: 2SLS Estimation Results for PoS=‘D’, $MktSegType$=‘FrstAdvn’, $SatStay$=0, $TimeSlot = 2$

C.11 OLS and 2SLS Results for Inbound Trips, First Class Late Purchases

In the following figures, for each classification group based on $SatStay$ and $TimeSlot$ under PoS = 'D', $MktSegType$ = 'FrstLate', we first provide the results from the stepwise OLS estimation followed by the results from the 2SLS estimation.

The REG Procedure
Model: MODEL1
Dependent Variable: LN_PAX

Number of Observations Read	1763
Number of Observations Used	1763

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	14	207.96616	14.85473	54.46	<.0001
Error	1748	476.81888	0.27278		
Corrected Total	1762	684.78504			

Root MSE	0.52228	R-Square	0.3037
Dependent Mean	0.52701	Adj R-Sq	0.2981
Coeff Var	99.10301		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	0.13207	0.04929	2.68	0.0074	0
LN_PRATIO	1	0.15121	0.03384	4.47	<.0001	1.08555
LN_LAG_PAX	1	0.11993	0.02313	5.18	<.0001	1.36471
PUBHOL	1	0.22866	0.07976	2.87	0.0042	1.19877
RDD6	1	0.38501	0.03974	9.69	<.0001	1.02212
RDDINDEX	1	0.01049	0.00398	2.64	0.0084	1.07010
SUN	1	0.47163	0.04337	10.87	<.0001	2.36092
MON	1	0.31163	0.04314	7.22	<.0001	2.06816
WED	1	-0.11777	0.05173	-2.28	0.0229	1.54617
THU	1	-0.15946	0.05526	-2.89	0.0040	1.45246
FRI	1	-0.19627	0.05729	-3.43	0.0006	1.41799
SAT	1	-0.09813	0.05322	-1.84	0.0654	1.51923
AUG	1	-0.18176	0.04528	-4.01	<.0001	1.03160
NOV	1	0.12874	0.04297	3.00	0.0028	1.02314
LN_AVGCONN	1	0.09479	0.03117	3.04	0.0024	1.02248

Figure 91: Stepwise OLS Estimation Results for PoS='D', $MktSegType$='FrstLate', $SatStay$=1, $TimeSlot$ = 1

Two-Stage Least Squares Estimation

Model	LN_PAX
Dependent Variable	LN_PAX

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	14	202.5211	14.46580	51.54	<.0001
Error	1748	490.5669	0.280645		
Corrected Total	1762	684.7850			

Root MSE	0.52976	R-Square	0.29220
Dependent Mean	0.52701	Adj R-Sq	0.28653
Coeff Var	100.52156		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	0.165989	0.273736	0.61	0.5443
LN_PRATIO	1	-0.08905	1.906684	-0.05	0.9628
LN_LAG_PAX	1	0.122133	0.029259	4.17	<.0001
PUBHOL	1	0.249731	0.185739	1.34	0.1790
RDD6	1	0.392220	0.069973	5.61	<.0001
RDDINDEX	1	0.005793	0.037485	0.15	0.8772
SUN	1	0.517686	0.368104	1.41	0.1598
MON	1	0.319542	0.076548	4.17	<.0001
WED	1	-0.10947	0.084208	-1.30	0.1938
THU	1	-0.15852	0.056556	-2.80	0.0051
FRI	1	-0.20384	0.083598	-2.44	0.0149
SAT	1	-0.09542	0.058089	-1.64	0.1006
AUG	1	-0.17951	0.049278	-3.64	0.0003
NOV	1	0.131358	0.048292	2.72	0.0066
LN_AVGCONN	1	0.090994	0.043690	2.08	0.0374

Hausman's Specification Test Results

Comparing	To	DF	Statistic	Pr > ChiSq
OLS	2SLS	14	0.65	1.0000

Figure 92: 2SLS Estimation Results for PoS=‘D’, $MktSegType$=‘FrstLate’, $SatStay$=1, $TimeSlot = 1$

The REG Procedure
Model: MODEL1
Dependent Variable: LN_PAX

Number of Observations Read 2374
Number of Observations Used 2374

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	14	1074.58092	76.75578	213.99	<.0001
Error	2359	846.14076	0.35869		
Corrected Total	2373	1920.72168			

Root MSE	0.59890	R-Square	0.5595
Dependent Mean	0.94831	Adj R-Sq	0.5569
Coeff Var	63.15466		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	0.02484	0.04150	0.60	0.5496	0
LN_PRATIO	1	0.32446	0.03821	8.49	<.0001	1.15402
PUBHOL	1	0.56376	0.07890	7.15	<.0001	1.12995
RDD6	1	0.42138	0.04052	10.40	<.0001	1.01292
RDDINDEX	1	0.04335	0.00389	11.14	<.0001	1.08874
SUN	1	1.11821	0.04515	24.77	<.0001	2.41954
MON	1	0.26491	0.03783	7.00	<.0001	1.35333
WED	1	-0.09969	0.04123	-2.42	0.0157	1.25595
THU	1	-0.08466	0.04015	-2.11	0.0351	1.27029
FEB	1	0.09880	0.04336	2.28	0.0228	1.04648
AUG	1	-0.12648	0.04402	-2.87	0.0041	1.05203
NOV	1	0.10498	0.04290	2.45	0.0145	1.04934
DEC	1	-0.10901	0.04469	-2.44	0.0148	1.04750
LN_AVGCONN	1	0.11167	0.03907	2.86	0.0043	1.01805

Figure 93: Stepwise OLS Estimation Results for PoS=‘D’, $MktSegType$=‘FrstLate’, $SatStay$=1, $TimeSlot = 2$

Two-Stage Least Squares Estimation

Model	LN_PAX
Dependent Variable	LN_PAX

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	15	1051.464	70.09761	134.39	<.0001
Error	2358	1229.901	0.521587		
Corrected Total	2373	1920.722			

Root MSE	0.72221	R-Square	0.46089
Dependent Mean	0.94831	Adj R-Sq	0.45746
Coeff Var	76.15725		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	0.250279	0.098676	2.54	0.0113
LN_PRATIO	1	-0.93068	0.464687	-2.00	0.0453
LN_LAG_PAX	1	0.199293	0.024025	8.30	<.0001
PUBHOL	1	0.802881	0.128943	6.23	<.0001
RDD6	1	0.451558	0.050091	9.01	<.0001
RDDINDEX	1	0.013669	0.011901	1.15	0.2509
SUN	1	1.418188	0.122885	11.54	<.0001
MON	1	0.363235	0.058335	6.23	<.0001
WED	1	-0.10320	0.049729	-2.08	0.0381
THU	1	-0.06152	0.049272	-1.25	0.2120
FEB	1	0.119872	0.053251	2.25	0.0245
JUL	1	0.130405	0.063253	2.06	0.0394
AUG	1	-0.01364	0.066801	-0.20	0.8382
NOV	1	0.119380	0.052485	2.27	0.0230
DEC	1	-0.06719	0.056119	-1.20	0.2314
LN_AVGCONN	1	0.137369	0.048086	2.86	0.0043

Figure 94: 2SLS Estimation Results for PoS =‘D’, $MktSegType$=‘FrstLate’, $SatStay$=1, $TimeSlot = 2$

The REG Procedure
Model: MODEL1
Dependent Variable: LN_PAX

Number of Observations Read 2347
Number of Observations Used 2347

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	16	445.98877	27.87430	65.50	<.0001
Error	2330	991.55167	0.42556		
Corrected Total	2346	1437.54044			

Root MSE	0.65235	R-Square	0.3102
Dependent Mean	0.91427	Adj R-Sq	0.3055
Coeff Var	71.35191		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Variance Inflation
Intercept	1	1.16159	0.05560	20.89	<.0001	0
LN_PRATIO	1	0.24365	0.06149	3.96	<.0001	1.02629
LN_LAG_PAX	1	0.13500	0.02019	6.69	<.0001	1.40523
PUBHOL	1	-0.32491	0.12639	-2.57	0.0102	1.03844
RDD6	1	0.42679	0.04441	9.61	<.0001	1.04614
RDD7	1	0.31557	0.04667	6.76	<.0001	1.04521
RDD1	1	-0.48009	0.05212	-9.21	<.0001	1.39544
RDDINDEX	1	-0.07476	0.00522	-14.33	<.0001	1.64081
SUN	1	-0.62287	0.06319	-9.86	<.0001	1.16890
MON	1	-0.22570	0.04748	-4.75	<.0001	1.24123
WED	1	0.21613	0.04197	5.15	<.0001	1.29025
THU	1	0.27547	0.04111	6.70	<.0001	1.31766
FRI	1	0.24301	0.04095	5.93	<.0001	1.32835
MAY	1	-0.10473	0.04797	-2.18	0.0291	1.03383
JUL	1	-0.16532	0.04622	-3.58	0.0004	1.03317
AUG	1	-0.49807	0.06099	-8.17	<.0001	1.06555
LN_AVGCONN	1	0.10949	0.03761	2.91	0.0036	1.03220

Figure 95: Stepwise OLS Estimation Results for PoS='D', $MktSegType$='FrstLate', $SatStay$=0, $TimeSlot$ = 1

Two-Stage Least Squares Estimation

Model	LN_PAX
Dependent Variable	LN_PAX

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	17	441.5164	25.97156	33.77	<.0001
Error	2329	1791.138	0.769059		
Corrected Total	2346	1437.540			

Root MSE	0.87696	R-Square	0.19775
Dependent Mean	0.91427	Adj R-Sq	0.19190
Coeff Var	95.91922		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	1.154914	0.100915	11.44	<.0001
LN_PRATIO	1	2.918608	3.325354	0.88	0.3802
LN_LAG_PAX	1	0.125502	0.029568	4.24	<.0001
PUBHOL	1	-0.31740	0.182576	-1.74	0.0823
RDD6	1	0.454080	0.072502	6.26	<.0001
RDD7	1	0.304381	0.064242	4.74	<.0001
RDD1	1	-0.37470	0.152969	-2.45	0.0144
RDDINDEX	1	-0.06373	0.015588	-4.09	<.0001
SUN	1	-0.39805	0.340359	-1.17	0.2423
MON	1	-0.25900	0.073002	-3.55	0.0004
WED	1	0.171673	0.066595	2.58	0.0100
THU	1	0.246194	0.066231	3.72	0.0002
FRI	1	0.189552	0.067686	2.80	0.0051
SAT	1	0.177909	0.316518	0.56	0.5741
MAY	1	-0.07374	0.074554	-0.99	0.3228
JUL	1	-0.09460	0.105793	-0.89	0.3713
AUG	1	-0.40206	0.144543	-2.78	0.0055
LN_AVGCONN	1	0.170266	0.089430	1.90	0.0570

Figure 96: 2SLS Estimation Results for PoS = ‘D’, $MktSegType$=‘FrstLate’, $SatStay$=0, $TimeSlot = 1$

```
                         The REG Procedure
                           Model: MODEL1
                    Dependent Variable: LN_PAX

             Number of Observations Read        3374
             Number of Observations Used        3374


                        Analysis of Variance

                                   Sum of           Mean
Source                   DF       Squares         Square    F Value    Pr > F

Model                    14    2632.89998      188.06428     202.29    <.0001
Error                  3359    3122.77364        0.92967
Corrected Total        3373    5755.67362


           Root MSE              0.96420    R-Square     0.4574
           Dependent Mean        1.89932    Adj R-Sq     0.4552
           Coeff Var            50.76523


                        Parameter Estimates

                          Parameter       Standard                                  Variance
Variable          DF       Estimate          Error    t Value    Pr > |t|          Inflation

Intercept          1        2.53941        0.06686      37.98      <.0001                  0
LN_PRATIO          1        0.17883        0.05487       3.26      0.0011            1.07094
LN_LAG_PAX         1        0.11860        0.01654       7.17      <.0001            1.65788
PUBHOL             1       -1.41363        0.13009     -10.87      <.0001            1.07274
RDD6               1        0.76544        0.05872      13.04      <.0001            1.03195
RDD7               1        0.56284        0.06177       9.11      <.0001            1.02285
RDDINDEX           1       -0.09339        0.00511     -18.28      <.0001            1.14436
SUN                1       -1.57695        0.06167     -25.57      <.0001            1.48593
MON                1       -0.44016        0.05330      -8.26      <.0001            1.16448
WED                1        0.08855        0.04983       1.78      0.0757            1.13394
SAT                1       -1.41195        0.05803     -24.33      <.0001            1.40195
FEB                1        0.10118        0.05968       1.70      0.0901            1.02520
AUG                1       -0.62401        0.06143     -10.16      <.0001            1.06572
DEC                1       -0.18208        0.05904      -3.08      0.0021            1.03086
LN_AVGCONN         1        0.39479        0.06091       6.48      <.0001            1.01720
```

Figure 97: Stepwise OLS Estimation Results for PoS='D', $MktSegType$='FrstLate', $SatStay$=0, $TimeSlot = 2$

Two-Stage Least Squares Estimation

Model	LN_PAX
Dependent Variable	LN_PAX

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	15	2628.637	175.2425	177.25	<.0001
Error	3358	3320.060	0.988702		
Corrected Total	3373	5755.674			

Root MSE	0.99433	R-Square	0.44188
Dependent Mean	1.89932	Adj R-Sq	0.43939
Coeff Var	52.35205		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	2.505910	0.069932	35.83	<.0001
LN_PRATIO	1	-0.62072	0.264879	-2.34	0.0192
LN_LAG_PAX	1	0.117277	0.017065	6.87	<.0001
PUBHOL	1	-1.35211	0.135555	-9.97	<.0001
RDD6	1	0.750895	0.060748	12.36	<.0001
RDD7	1	0.574887	0.063824	9.01	<.0001
RDDINDEX	1	-0.09881	0.005553	-17.79	<.0001
SUN	1	-1.41761	0.081846	-17.32	<.0001
MON	1	-0.43071	0.055110	-7.82	<.0001
WED	1	0.086193	0.051401	1.68	0.0937
SAT	1	-1.33061	0.065347	-20.36	<.0001
FEB	1	0.132984	0.062617	2.12	0.0338
AUG	1	-0.60262	0.063977	-9.42	<.0001
NOV	1	-0.01746	0.063320	-0.28	0.7828
DEC	1	-0.20598	0.062019	-3.32	0.0009
LN_AVGCONN	1	0.467800	0.067104	6.97	<.0001

Figure 98: 2SLS Estimation Results for PoS = ‘D’, $MktSegType$=‘FrstLate’, $SatStay$=0, $TimeSlot = 2$

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